DO THEY KNOW?

A STUDY OF THE IMPACT OF PDMR TRANSACTIONS ON STOCK MARKET RETURNS DURING THE UNCERTAIN MARKET CONDITIONS OF THE COVID-19 PANDEMIC

EDVARD BRUU

ALEXANDER SILWER

Bachelor Thesis

Stockholm School of Economics

2022

Do They Know?: A Study of the Impact of PDMR Transactions on Stock Market Returns During the Uncertain Market Conditions of the Covid-19 Pandemic

Abstract

This paper examines how equities listed on Nasdaq Stockholm reacted to transaction announcements by persons discharging managerial responsibilities ("PDMRs") during unprecedented market uncertainty. We find that PDMRs transaction announcements generated abnormal returns for purchases but not for sales. We then investigate what factors that are explanatory and run analyses across various company sizes. We identify that PDMR transaction announcements carry informational value, and that the magnitude of the informational value was elevated during the Covid-19 pandemic. This paper validates prior studies and opens for further research on regulatory initiatives to level the playing field between regular investors and corporate insiders.

Keywords

Covid-19, Insider Trading, Nasdaq Stockholm, Uncertainty, PDMR

Authors

Edvard Bruu (24811)

Alexander Silwer (24696)

Tutors

Marieke Bos, Deputy Director, Swedish House of Finance

Examiner

Adrien d´Avernas, Assistant Professor, Department of Finance, Stockholm School of Economics

Acknowledgements

We direct our gratitude toward Marieke Bos for excellent guidance, kind support, and helpful comments. We would also like to thank Gustaf Soldan for support and guidance with the statistical analysis. All errors are those of the authors.

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

ON THE 20TH OF FEBRUARY 2020, OMXSPI – an index of all shares that trade on the Stockholm Stock Exchange reached an all-time high (Nasdaq, 2022a). Twenty-five calendar days later, on the 16th of March, the index had lost more than 35 percent of its value. The rapid fall was a consequence of the increased spread of the novel coronavirus, SARS-CoV-2. By the 18th of March, lockdown measures to halt the escalation were widespread and more than 250 million people in Europe were under strict lockdowns (The Guardian, 2020). The number of PDMR transactions in companies listed on Nasdaq Stockholm increased with 291% year-over-year in the month of March, between 2019 and 2020 (SFSA, 2022). More generally, the frequency of trades trended upwards throughout the entire period of 2017-2021 (Graph 1). In this study, we investigate how prices of equities listed on Nasdaq Stockholm react to insider transactions and how the reactions change during uncertain market environments.

In 2020, there was extreme uncertainty in financial markets globally (Baker et al, 2016). The Covid-19 pandemic was an event with unprecedented uncertainty both in terms of magnitude and duration. At its peak, it was an existential crisis, far worse than what the world encountered during the financial crisis of 2008-09 (McKinsey, 2020). In April 2020, IMF projected full-year US GDP to contract -5.9%, revised to -8.0% in May, actual outcome was -3.5% (IMF, 2020).

At the same time, trading activity among insiders in Swedish companies was at highly elevated levels. Legal insider transactions occur when a person discharging managerial responsibilities ("PDMR") purchases or sells financial instruments where he or she does not know about any upcoming material market announcement (e.g., earnings, M&A, other material events). Not to be confused with illegal insider transactions, which occur when PDMRs use their knowledge to profit from known upcoming market announcements. In practice, the PDMR transaction is generally legal when it follows the ruling guidelines and there is no guaranteed (or highly certain) profit to be derived in the short run.

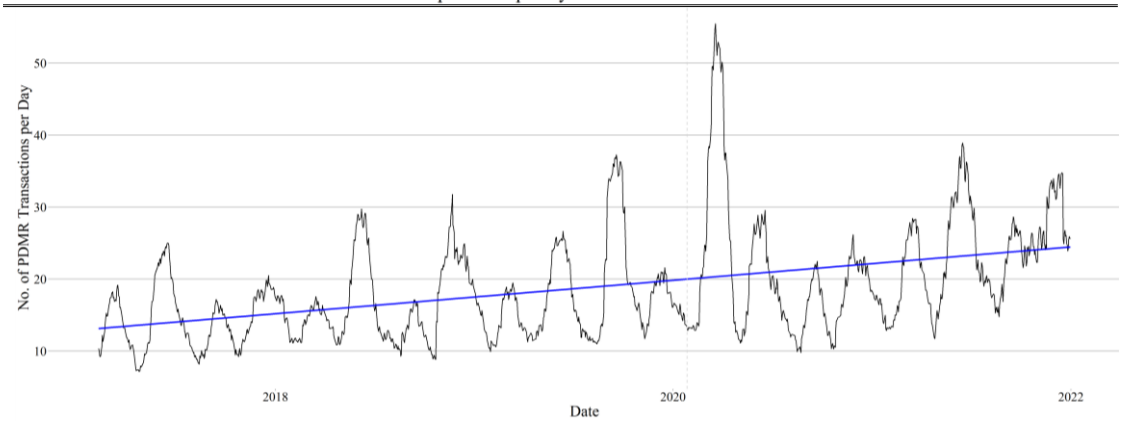
Market reactions to PDMR transaction announcements are important to study as they can be used as a proxy to put a number on the value of the informational advantage held by PDMRs. Markets tend to react more positively to PDMR purchases than to PDMR sales (Lakonishok and Lee, 2001). Large market reactions following a PDMR transaction announcement indicate a greater informational value of said transaction. A PDMR that believes that the stock price of his or her company has a strong outlook can be expected to purchase more shares and vice versa. There is an informational value of PDMR transactions as PDMRs have greater visibility on upcoming company performance compared to other market actors, which is also why PDMR transactions are regulated.

If an uncertain market environment can be shown to elevate the advantage of PDMRs, then it may be of interest for regulators to further restrict PDMR trading during these conditions, which is why this study is of interest.

Graph 1 shows an initial spike of trades during the rapid decline of the market in Q1 2020, as well as a general elevation of trading volumes throughout 2020 and 2021. The cyclical pattern of transactions should be seen in the light of the trading restrictions that are posed on PDMRs before the release of earnings

results; known as the "silent period" (Swedish Financial Supervisory Authority, 2022).

Graph 1. Frequency of PDMR Transactions



The graph above illustrates the trading frequency among PDMRs at Nasdaq Stockholm in the period 2017-2021 (black line), calculated as a 30-day rolling average of PDMR transaction volumes. In addition, a trend line for this frequency data across the period is also included in the graph (blue line). The vertical grey line indicates the split of our control and treatment periods.

(SFSA, 2022)

In Sweden, the PDMR rules are set forth by the Swedish Financial Supervisory Authority ("SFSA"). Any transaction that falls under the rules must be reported within three business days. Information about transactions is generally made available to the public immediately upon reporting. The SFSA has been tracking all reported PDMR transactions since 1995. PDMRs report their transactions directly to the SFSA and any person subject designated as a PDMR and has an annual trading volume of at least EUR 5,000 is required to report all of their transactions. PDMRs are heavily restricted in terms of timing for their purchases and sales (SFSA, 2022).

The market reactions to PDMR transactions in normal market conditions has been thoroughly studied in prior research. By combining the research question asked by Lakonishok and Lee (2001) and the methodology used by Loh and Stulz (2018) in their study of market reactions to analyst revisions in uncertain market conditions, our study covers a field that has seen limited research. We have not found, foreign or domestic, any papers that study how the market reacted to PDMR transactions during an event with equivalent uncertainty as the Covid-19 pandemic. Hence, we hope that the study will be seen as an appreciated addition to current literature.

In this study, we investigate how stocks listed on Nasdaq Stockholm reacted to PDMR transaction announcements during a period with higher market uncertainty (approximately 2020 to 2021) as opposed to a period with lower market uncertainty (2017 to 2019). To achieve this, we formulate the following two research questions:

I) Was there a higher informational value of PDMR trading during the Covid-19 period as compared to normal market conditions?

II) What parameters affect how much the informational value deviated during the Covid-19 period as compared to normal market conditions?

This study is a natural build-on to previous studies closely related to this topic. Lakonishok and Lee (2001) found that insider trades have an informative value, and we wish to build on this by investigating how this effect change

depending on market sentiment. A lot of research has been made around investor sentiment in terms of uncertainty, but little has been made on how PDMR transactions affect markets across good and bad sentiments. Covid-19 is for natural reasons a relatively new research topic, and we find this study to complement existing research well.

To structure the report, we will base our analysis on Loh and Stulz (2018). They studied market reactions to research analyst revisions during good and bad times. They found that analyst ratings play a more important role during times of high uncertainty. The fundamentals of their study are highly transferable to our study given that they also look at the informational value of condensed information released collectively to the market, while also making a distinction between normal market conditions and times of uncertainty.

In our study, we have been using two sets of data. The first data set is from the SFSA and consists of all reported PDMR transactions from the beginning of 2017 to the end of 2021. Every PDMR transaction report includes descriptions of the particular transaction concerning its nature and included stakeholders. The second data set is from Refinitiv and consists of opening and closing stock prices covering one period before and after each PDMR transaction in the first data set, as described in the Data Section. The study only includes Nasdaq Stockholm (Large Cap, Mid Cap, Small Cap, and First North).

We have opted to replicate the methodology of Loh and Stulz (2018). For every PDMR transaction report, a quantitative analysis has been made to assess whether the related stock has seen abnormal stock returns following the publication of the PDMR transaction. Abnormal returns have been defined in relation to industry price indices. We have then compared the results across the Covid-19 period (treatment period) and the period of normal market conditions (control period). Like Loh and Stulz (2018) we conducted a Welch's t-test to compare the populations, followed by a time-series regression.

The results show higher abnormal stock returns following PDMR purchase transaction reports in the treatment period than in the control period. Across all markets, the difference between the periods equals 0.39% (p-level<0.01) for purchases. We have not seen a meaningful difference in price impact from sales. Overall, the largest impact was seen in the industry group "Banks." Additionally, through the time-series regression, we were able to isolate the effect of the uncertainty factor to a greater extent. Full results will be elaborated on in a later section.

Theory and Hypotheses

A. Background

To explain how, and why the market reacts to insider trades, this section provides the theoretical framework through which the matter can be understood. The section is divided into four parts. Our first section covers previous research on investor behaviors in times of uncertainty (i.e., if the information can be expected to be incorporated the same way during times of high uncertainty). In this section, we also include our main reference, Loh and Stulz (2018). The second section covers how markets can be expected to react to announcements of PDMR transactions (i.e., how, and when the information value is incorporated in prices). In the third section, we review the informativeness of insider trading. In the

fourth section, the contribution of this report will be discussed, and how it complements previous research. Finally, in the last section we discuss our hypotheses for the results of our research.

B. Times of Uncertainty

The Covid-19 pandemic was an unprecedented event during which the level of uncertainty in global markets reached a record high (Baker et al. 2016). In the third issue of the 73rd volume of The Journal of The American Finance Association, Loh and Stulz published their study "Is Sell-Side Research More Valuable in Bad Times?". Their study was set up to find out if analyst revisions had a more influential impact on stock prices during times of uncertainty. To define times of uncertainty, they used the definition set forth by Baker et al. (2016). In addition to utilizing the Economic Policy Uncertainty Index, they also added additional periods of defined crises. These were September – November 1987 (1987 Crisis), August – December 1998 (LTCM), and July 2007 – March 2009 (GFC). They laid out three hypotheses for why analysts may have less of an impact during times of uncertainty and three hypotheses for why analysts may have more impact during times of uncertainty. We will elaborate on these hypotheses to the extent that they can be related to our study.

The most prominent argument for why analysts would have less impact during times of uncertainty is the inattention hypothesis. In a study from 2009, Hirshleifer, Lim and Teoh showed that when a lot going on in the markets (measured as intensity of news flow), investors are inclined to not be heavily affected by news events. This could analogously be applied to our study. There are evident similarities between reporting of PDMR transactions and reporting of updated analyst revisions. This follows logically as both cases are based on someone who can be presumed to possess a high level of knowledge taking an action that can be perceived as being more (i.e., an upwards revision or a purchase) or less (i.e., a downwards revision or a sale) positive. The logical argument holds up better for purchases than for sales. In his book "One Up On Wall Street", Peter Lynch states that insiders sell stocks for many reasons, but there is only one reason that they purchase stocks – to make money. If the hypothesis of Loh and Stulz (2018) holds and if their reasoning can be analogously applied, then we could expect to see little to no additional impact from when PDMR transactions are made during times of uncertainty as compared to times without uncertainty.

In favor of why analysts (and analogously PDMRs) would have more impact during times of uncertainty are two main concepts. Firstly, Schmalz and Zhuk (2019) showed that some firms see greater stock price reactions to announcements during bad times. This effect is attributed to the overreaction hypothesis. Secondly, Kacperczyk et al. (2017) proved that information on future payoffs that are of reasonable accuracy has a higher informational value when there is a lot of uncertainty. Following the logic from prior concepts, then this would indicate that PDMR transactions would have a greater stock price impact during times of uncertainty.

In an interesting study by Hirshleifer and Shumway (2003), it was found that sunny days are strongly correlated with abnormal returns. There was no effect from other weather conditions. They suggest that sunlight affected the mindsets

of people which resulted in more positive sentiment. Loewenstein (1996) found that being "out of control" in terms of fulfilling the visceral factors of oneself had direct effects on impulsivity and self-control. Both these studies confirm that investor sentiment is easily affected by externalities.

Chiu, Chung, Ho and Wu (2018) found that a strong negative sentiment resulted in net-selling in the market, putting pressure on prices. If we can say that the uncertainty of the pandemic gave people a sense of being "out of control", then we should see increased sales pressure in the market. Combined with the findings of Christie and Huangs (1995) that investors are more prone to follow others during times of crisis, we find a literature indication that PDMR transactions may have a greater impact during times of crisis.

C. Real-time Event Impact on Capital Markets

Starting with Fama (1970), security prices in an efficient market reflect all available information. Efficiency can be in the weak form (prices reflect all public historical information), in semi-strong form (prices reflect all public historical and current information), or in strong form (prices reflect all public and private historical and current information). Equity markets are generally operating under semi-strong efficiency. Under the efficient market assumption, we should therefore expect PDMR transactions to have an immediate effect on stock prices since PDMR transactions, as identified by Lakonishok and Lee (2001), can be used to predict stock price performance.

Busse and Green (2002) found that a stock being mentioned in a positive manner would see abnormal returns immediately (within seconds). They found that active traders play an important role in ensuring that prices respond quickly to information. Belgacem, Creti, Guesmi and Lahiani (2015), found that macroeconomic announcements had an immediate effect on the US stock market which in turn had an immediate effect on the oil market. Mehndiratta and Gupta (2010) showed that the stock market had an immediate reaction to dividend announcements. These studies show that markets re-price stocks following material announcements and can hence not explain what Lakonishok and Lee (2001) saw as markets missing out on valuable information. While this study will not review the long-term effects of PDMR transactions, it will review its short-term effect.

D. Informativeness of PDMR Transactions

PDMR purchasing activities tend to be an indicator of upcoming abnormal stock returns (Alldredge and Cicero, 2015). Lakonishok and Lee (2001) examined all PDMR activity for all companies on the NYSE and Nasdaq during a twenty-year period. As they expected that it could take some time for reporting information to reach markets, they decided to look at returns during a 5-day window. They could conclude that PDMRs achieved abnormal returns on their purchases in some cases whereas they did not in other cases. Most of the short-term returns occurred following the trading date rather than following the publication of their trades. The greatest effect was seen when a manager or executive purchased stocks in a small company, yielding almost a 0.75% abnormal return over the upcoming 5-day period. Another quarter percentage of abnormal returns was added in the 5 days following the publication of the PDMR transaction. A manager or executive buying in large companies had little effect.

By combining the effect of the 5-day period following the trade and the 5 days following the announcement, they showed that the market responded with around one percentage abnormal returns for small companies and close to no abnormal returns for large companies. Their results were in line with previous studies (Seyhun, 1986) however for Eckbo and Smith (1998) PDMRs did not earn immediate abnormal returns in their study of transactions at the Oslo Stock Exchange.

When Lakonishok and Lee (2001) reviewed long-term stock performance following PDMR transactions, they found that transactions were useful for predicting long-term returns. They found that a company with extensive insider purchases performed 7.8% better than companies with extensive insider sales during the first year. The spread shrunk to 2.3% in the second year. In the article, they also concluded that it was unlikely that the difference in performance could be attributed to different risk profiles of each respective equity. Their main conclusion was that insiders are great at picking up shares at a lower price and seem to know when to sell. Most interestingly, they also found that the market does not react immediately to incorporate the full predictive value of insider transactions, hinting that valuable information is ignored by the market.

Biggerstaff, Cicero and Wintoki (2020) found that PDMRs trade both when they have a short-term informational advantage and when they have a long-term advantage. They provide an example with two firms: one that is about to miss on earnings in the near future and one that has an ongoing process with a supplier that is developing poorly but will not be revealed to the market for many months. At the first firm, the insider has only a short amount of time to trade before it will be too late. In the latter case, the insider has a long duration to trade before the market will punish the stock price. To account for this, the authors are considering two types of trades: isolated and sequenced. They conclude that both have strong informational value. They also concluded that the informational advantage could be derived from being more aware and informed of external activities relating to the business performance (e.g., early spotting of trends such as upcoming supply chain issues). In other words, abnormal returns by PDMRs do not necessarily stem from direct information their own companies but could also stem from being more aware of public information about related parties.

Table 1. Mapping of Select Literature

	Author	Year	Focus area	Market Reactions	PDMR	Uncertainty	Market
Main references	Loh and Stulz	2018	Market reactions to analyst revisions	✓	-	✓	US
	Lakonishok and Lee	2001	Informativeness of insider trading	✓	✓	-	US
Selected other references	Biggerstaff, Cicero and Wintoki	2020	Informativeness of insider trading	✓	✓	-	US
	Schmalz and Zhuk	2019	Market reactions to corporate annoncements…	✓	-	✓	US
	Chiu, Chung, Ho and Wu	2018	Equity prices during weak sentiments	✓	-	✓	US
	Baker et al.	2016	Uncertainty	-	-	✓	Global
	Belgacem, Creti, Guesmi and Lahiani	2015	Market reactions to real time events	✓	-	-	US
	Kacperczyk	2015	Value of information during uncertainty	✓	-	✓	US
	Mehndiratta and Gupta	2010	Market reactions to corporate events	✓	-	-	US
	Hirshleifer, Lim and Teoh	2009	Market reactions during high noise	✓	✓	-	US
	Busse and Green	2002	Market reactions to real time events	✓	-	-	US
	Eckbo and Smith	1998	PDMR trading	✓	✓	-	NO
	Christie and Huang	1995	Uncertainty	✓	-	✓	US
	Seyhun	1986	PDMR trading	✓	✓	-	US
	Fama	1970	Efficient market hypothesis	✓	-	-	US

The table above shows a summary of a select number of literary references used in this paper and what combinations of content they cover. As seen there is no current paper that researches the intersection of the market reaction to PDMR transactions in times of uncertainty.

E. Contribution

Our work is the first report that reviews how uncertain times affect market reactions to PDMR transactions. Lakonishok and Lee (2001) asked whether PDMR transactions are informative, which they did indeed find them to be. We ask whether PDMR transactions carry additional informative value during times of uncertainty. To further build on their study, we will add additional control variables beyond PDMR ranking and company size. In difference to Lakonishok and Lee (2001), we will study Nasdaq Stockholm as opposed to the New York Stock Exchange, Nasdaq, and American Stock Exchange. We estimate that the dynamics of Loh and Stulz (2018) will be similar to our study subject and hence construct our methodology to resemble their work. We use Loh and Stulz (2018) as they also reviewed a period with a distinct uncertain market environment with more stable periods.

F. Hypotheses

To address our two research questions, we present three main hypotheses that we will test with the data set.

Hypothesis 1:

There will be an increased market reaction to PDMR transactions for the Covid-19 period.

In Loh and Stulz (2018), bad times contributed significantly to increased market reactions to analyst revisions. We expect the same to hold for our study. This is also in line with with Schmalz and Zhuk (2019) and Kacperczyk et al. (2017).

Hypothesis 2:

The intensity of the increased market reactions will vary across sectors. We expect to see greater market reactions among stocks in the industries: 'Automobiles and Parts', 'Energy' and 'Travel and Leisure'

The probability of default report from S&P (Standard & Poor's, 2022) can be used as a proxy to predict which sectors that have had the worst sentiment and therefore should see the largest reaction. Based on their report, we expect the market reactions to be most exaggerated for Travel and Leisure (~19% peak default risk), Automobiles (~14% peak default risk) and Energy (~13% peak default risk) (Standard & Poor's, 2022). Furthermore, sectors with greater uncertainty are probably more likely to have investors that are in a sense of being "out of control" (Loewenstein, 1996). The sentiment should be worse in sectors that are harder hit by the pandemic (Chiu et al, 2018). Worse sentiments would imply that PDMR transactions should therefore have more pronounced increased market reactions.

Hirshleifer, Lim and Teoh (2009) found that a high intensity of investor updates caused each incremental update to have a relatively smaller impact. We expect corporations in sectors with a greater Covid-19 exposure to serve their investors with fewer updates (i.e., suspended guidance, hesitancy to comment on outlooks). Hence, we expect a larger informational advantage for insiders in these sectors and therefore a higher intensity of market reaction to PDMR transaction announcements. This would apply to the sector 'Travel and Leisure'.

Hypothesis 3:

Reactions to stocks listed on markets with looser regulation requirements will be larger. This implies that we expect reactions on Nasdaq First North to be greater than on the Main List of Nasdaq Stockholm.

Biggerstaff, Cicero and Wintoki (2020) conclude that PDMRs trade when they have an informational advantage. The value of the informational value should, following a PDMR transaction, be incorporated into the stock price assuming semi-strong market efficiency (Fama, 1970). We think that the value of PDMRs informational advantages increases during bad times and as such any trade should cause more of an increased market reaction. More importantly, we think that the relative informal advantage is greater in small companies listed on markets with looser reporting requirements. The two main drivers for this are less comprehensive investor communication and less analyst coverage (Nasdaq, 2021a). Additionally, this is also in line with the findings of Alldredge and Cicero (2015).

Data

A. Background

To investigate our research question, we leverage two sets of data. Data from the SFSA on PDMR transactions over the period stretching from January 2017 to December 2021 and market data for the same period. The market data is required to assess market reactions to PDMR transactions. In this section, the data approach utilized for this paper will be further detailed.

B. Ideal Data Set

In an ideal world, our research question would be studied by looking at companies with identical characteristics, evenly spread between different sectors, where some companies are randomly assigned market conditions that are classified as uncertain, hence synthetically creating an exogenous change in uncertainty. These companies would then have similar PDMR transaction behavior, unaffected by personal biases or company differences, with consistent publication patterns of these transactions. This would enable us to make a cross-sectional analysis over time to observe these two groups of companies, and to study the potential difference in the endogenous change to their abnormal stock returns. The impact of the market uncertainty would hence be isolated and conclusions regarding its effect on the informational value that the market assigns to such conditions would be highly precise. However, in practice, it would be impossible to gather such data and conduct the research in this way. Hence, we have had to adhere to the data that we have been able to gather in practice, the process of which is described below. Nonetheless, the reader should be aware that this entails inherent limitations to the conclusions that can be drawn from our results. These limitations include, but are not limited to, time trends, omitted variable bias, and problems with sector comparability. The impact of which will be discussed in detail in the Limitations Section.

C. PDMR Transaction Data

Most jurisdictions have restrictions on personal trading for people with insider information. In Sweden, these restrictions are regulated by the SFSA.

Information is collected based on EU Regulation No 596/2014 (MAR) Article 17. Article 19(10) of MAR defines who are covered under the regulation.

"(a) a member of the administrative, management, or supervisory body of that entity; or (b) a senior executive who is not a member of the bodies referred to in point (a), who has regular access to inside information relating directly or indirectly to that entity and power to take managerial decisions affecting the future developments and business prospects of that entity."

In addition, Article 3(1)(26) of MAR lists that any of the following also are covered provided that they have a connection with a person covered under Article 19(10) of MAR.

"(a) a spouse, or a partner considered to be equivalent to a spouse in accordance with national law, (b) a dependent child, in accordance with national law, (c) a relative who has shared the same household for at least one year on the date of the transaction concerned; or (d) a legal person, trust or partnership, the managerial responsibilities of which are discharged by a person discharging managerial responsibilities or by a person referred to in point (a), (b) or (c), or which is directly or indirectly controlled by such a person, or which is set up for the benefit of such a person, or the economic interests of which are substantially equivalent to those of such a person."

Covered persons must report transactions within three business days. It is mandatory to report the following information: link to PDMR (i.e., self or associated), position, name, issuer, type of instrument, ISIN code, type of transaction, link to option program, price per unit, volume, and transaction date. Following reporting, the SFSA immediately publishes the information without prior review (Official Journal of the European Union, 2014). Given that this system is based on self-reporting there are inherent problems with omitted or incorrect data for some transactions. Lakonishok and Lee (2001) based their data analysis on data exported from the Ownership Reporting System (ORS) from the U.S. Securities and Exchange Commission (SEC). This is the American equivalent to the Swedish system that the SFSA administrates, and has the same inherent self-reporting problem, hence being consistent with the methodology of this reference.

When extracting the PDMR transaction data from the Swedish Financial Supervisory Authority, certain data points were excluded due to incomplete data and lack of relevance to our research. Datapoints were filtered out in the following steps, with the number of transactions before and after the filter was applied specified in the parentheses:

I. Removal of non-share transactions, e.g., trades in options, warrants, and bonds, and non-trading transactions, e.g., loans and dividends (77,383 → 65,413).
II. Removal of transactions that have later been corrected or changed, where the updated version of the reporting has been included in the data set (65,413 → 59,116).
III. Removal of transfer transactions, where the PDMR has purchased and then sold the same number of shares on the same day to move these between accounts (59,116 → 58,394).

IV. Removal of transactions related to shares that are not listed on Nasdaq Stockholm (58,394 → 37,674).
V. Removal of transactions with incomplete information due to mistakes or inconsistencies in the reporting (37,674 → 31,240).

The decision to filter the data based on conditions 2 to 5 is aligned with the methodology of Lakonishok and Lee (2001). In their research, no data filtering was done based on financial instruments (step 1). Though that had to do with the fact that the data set exported from the U.S. Securities and Exchange Commission only contained stock transactions from the start, hence there was no need for these researchers to filter the data based on these conditions, which was necessary for us to do to achieve the equivalent data set.

D. Price Data

For every PDMR transaction, price data was collected from Refinitiv. The collection of pricing data was limited to opening and closing prices of the trading day that the publication of the PDMR transaction was made. In the case where a PDMR transaction was published outside of market opening hours, the methodology described in sub-section H was used to isolate the impact of the PDMR transaction on the abnormal market returns as much as possible.

The decision to use opening and closing prices of the trading day instead of intraday trading data stems from three factors. First, given that we wanted to look at PDMR transaction data across all Nasdaq Stock Exchange Lists, it would be challenging to set an appropriate time interval, given that the differing liquidity between the stock exchange lists would mean that the time it would take for the market prices to properly reflect the informational value of the PDMR transaction would differ between stock exchange lists. As we wanted to have a consistent methodology in our research, it would therefore be difficult to set an appropriate time interval without it being arbitrary and potentially missing the informational value contributed to the transaction. Second, given that we wanted to isolate the idiosyncratic changes in the stock value, which were not related to changes in general market or sector sentiment, we wanted to look at abnormal stock returns by adjusting with sector index development (will be described in sub-section H). However, intraday data for sector indices compiled by Nasdaq is not available, meaning that it would not be possible for us to isolate the abnormal stock return if looking at intraday data. Finally, the usage of opening and closing prices to analyze the abnormal stock returns in the market following an event with potential informational value is an approach that has been universally used among the references that we have looked at. This goes for both Lakonishok and Lee (2001) and Loh and Stulz (2018). Hence, to mimic this methodology as close as possible and avoid unintended consequences by deviating, opening, and closing prices were used as the price data in our research.

The PDMR reporting data set from the SFSA includes reports from all companies listed on Swedish regulated markets. For our study, we have narrowed down the scope to include companies listed on Nasdaq Stockholm. This includes Nasdaq Main Market and First North. The Main Market of Nasdaq Stockholm includes Large Cap, Mid Cap, and Small Cap. First North includes First North Growth Market and First North Premier Growth Market. For our

analysis, First North Growth Market and First North Premier Growth Market have been merged as they are of similar characteristics. Markets other than Nasdaq Stockholm have been excluded due to a general lack of transactional liquidity and inferior data quality, making it more difficult to draw conclusions through the inclusion of this data. The decision to exclude smaller stock exchange lists in the data analysis is also consistent with the methodology of Lakonishok and Lee (2001). In their case, they decided to limit their data set to PDMR transactions related to companies on the New York Stock Exchange (NYSE), approximately the American equivalent of Nasdaq Stockholm.

The sector indices used were based on the ICB-code (Industry Classification Benchmark) of the stock. For the Stockholm stock market, Nasdaq has a sector index for each of the industries categorized by the ICB codes. The index used for each sector is specified in Appendix B.

E. Stock Exchange Lists

To provide additional insight into the results and given our hypothesis that the degree of regulation and requirements regarding information sharing and transparency would have an impact on the informational value assigned to the PDMR transaction by the market, the transaction data was split according to the stock exchange list that the associated stock was listed on. This was also in line with the analysis conducted by Lakonishok and Lee (2001) which also made the equivalent split of the data to be able to draw more precise conclusions. Given that we limited the relevant transactions to stocks traded on the Nasdaq Stockholm stock exchange lists, there were four main stock exchange lists to split the transactions between Large Cap, Mid Cap, Small Cap, and First North, while also continuously looking at the aggregated level for all transactions, independent of stock exchange list.

The Nasdaq stock exchange lists differ in their requirements on company compliance, level of scrutiny on transparency, company size, and trading liquidity, which is what impacts the list chosen by the company during an IPO process (Nasdaq, 2019). It is also possible for companies to be transferred between stock exchange lists, given that they live up to the requirements of the new list. In those instances, we have classified the company according to the list that they were listed on as of December 31, 2021. The reason for this is that companies are expected to live up to the requirements of the new list several months before transferring, hence meaning that they in practice adhere to the requirements of the new list long before they are officially transferred (Nasdaq, 2021b). For the distinction between stock exchange lists it is therefore more reasonable to classify the stock according to the list it transferred to, rather than having it depend on the stock exchange list that the stock was listed on during the publication date, as the level of informational transparency will have been implemented in practice already. The number of unique companies and transaction dates included in the data set is showcased below, split by stock exchange list and transaction type.

Table 2. Descriptive Statistics - Companies & Transaction Dates

	Stock Exchange List				
	All Cap	Large Cap	Mid Cap	Small Cap	First North
No. of companies					
Purchases	828	128	146	94	460
Sales	579	112	112	69	286
No. of transaction dates					
Purchases	1,608	1,063	1,129	818	1,399
Sales	1,318	637	622	317	900

The table above shows the descriptive statistics for the number of unique companies traded and transaction dates in the data set. The data has been grouped by Stock Exchange Lists and split between transaction types.

F. Transaction Types

Finally, the dependent variable has also been split according to the transaction type, where a distinction has been made between PDMR purchase and sales transactions. The reasoning behind splitting the data into two subsets has to do with the inherent characteristics of the two different transaction types. As specified in the Hypothesis Section, we believe that a purchase from a PDMR of a security should generate a higher abnormal return of the share during times of uncertainty, while a sales transaction should generate a lower abnormal return, since this effect is expected to be negative. Hence, if these effects are equally large in opposite direction, we would only expect to see deviations from the control period that derives from differences in the relative weighting of the transaction types. To avoid the neutralization of informational value in the data set when mixing purchases and sales, we have instead opted to split the data between the two different transaction types to isolate these effects, while also allowing us to analyze the potential differences between the transaction types. This approach is also in line with the methodology used by Lakonishok and Lee (2001), where they also split the PDMR transactions between different transaction types and never analyzed the data on an aggregated level.

Table 3a. Descriptive Statistics Dependent Variables - PDMR Purchases

Variable	N	Mean	Median	Std. Dev.	Min	Max
All	**23,069**	**0.43%**	**0.17%**	**4.32%**	**-97%**	**46%**
Control	12,089	0.25%	0.08%	4.27%	-97%	38%
Treatment	10,980	0.64%	0.28%	4.36%	-49%	46%
Large Cap	**6,645**	**0.01%**	**0.01%**	**1.86%**	**-18%**	**28%**
Control	3,943	-0.06%	-0.04%	1.58%	-14%	18%
Treatment	2,702	0.10%	0.09%	2.20%	-18%	28%
Mid Cap	**4,213**	**0.30%**	**0.19%**	**3.32%**	**-33%**	**37%**
Control	2,339	0.16%	0.11%	2.81%	-26%	14%
Treatment	1,874	0.47%	0.30%	3.85%	-33%	37%
Small Cap	**2,210**	**0.62%**	**0.28%**	**4.09%**	**-18%**	**34%**
Control	1,231	0.57%	0.28%	3.88%	-18%	34%
Treatment	979	0.68%	0.25%	4.34%	-17%	16%
First North	**10,001**	**0.73%**	**0.35%**	**5.67%**	**-97%**	**46%**
Control	4,576	0.47%	0.25%	6.14%	-97%	38%
Treatment	5,425	0.95%	0.44%	5.23%	-49%	46%

The table above shows the descriptive statistics for the dependent variable for transactions on each stock exchange list and on an aggregated level for PDMR purchase transactions. The descriptive statistics are also split between the control and treatment period and shown on an aggregated level. Return is calculated as a change in price, expressed in percentage terms. The data is comprised of 23,069 purchase transactions across all stock exchange lists.

Table 3b. Descriptive Statistics Dependent Variables - PDMR Sales

Variable	N	Mean	Median	Std. Dev.	Min	Max
All	**8,171**	**-0.58%**	**-0.24%**	**4.93%**	**-96%**	**61%**
Control	4,139	-0.57%	-0.21%	5.58%	-96%	24%
Treatment	4,032	-0.60%	-0.27%	4.17%	-49%	61%
Large Cap	**2,204**	**0.06%**	**0.00%**	**1.93%**	**-11%**	**23%**
Control	1,080	0.20%	0.01%	1.91%	-11%	12%
Treatment	1,124	-0.06%	-0.02%	1.94%	-10%	23%
Mid Cap	**1,797**	**-0.77%**	**-0.45%**	**2.97%**	**-15%**	**15%**
Control	1,065	-1.10%	-0.55%	2.87%	-10%	14%
Treatment	732	-0.28%	-0.32%	3.04%	-15%	15%
Small Cap	**714**	**-0.41%**	**-0.07%**	**3.27%**	**-16%**	**11%**
Control	441	-0.48%	-0.09%	3.18%	-16%	6%
Treatment	273	-0.29%	-0.03%	3.42%	-13%	11%
First North	**3,456**	**-0.94%**	**-0.54%**	**6.92%**	**-96%**	**61%**
Control	1,553	-0.75%	-0.48%	8.44%	-96%	24%
Treatment	1,903	-1.09%	-0.57%	5.37%	-49%	61%

The table above shows the descriptive statistics for the dependent variable for transactions on each stock exchange list and on an aggregated level for PDMR sales transactions. The descriptive statistics are also split between the control and treatment period and shown on an aggregated level. Return is calculated as a change in price, expressed in percentage terms. The data is comprised of 8,171 sales transactions across all stock exchange lists.

G. Sector

With inspiration taken from Lakonishok and Lee (2001), we have also included a sector analysis in our research. Partly this has to do with the fact that it is reasonable for the market to attribute differing informational values to differing industries, given their varying characteristics. For example, as mentioned in our hypothesis regarding sectors, there is an inherent difference in default risk between industries that makes certain sectors more exposed in times of uncertainty.

Partly, we could also expect sector differences to exist due to the nature of the Covid-19 crisis, the effects of which have impacted industries to a varying degree. (Deloitte, 2020; Suneson, 2020) Given that the uncertainty during the treatment period is related to the unpredictability of the pandemic, it would be interesting to see if, and in that case how, the abnormal market returns vary between industries. Hence, we believe that a sector analysis will have a positive contribution to our research.

H. Dependent Variable: Abnormal Stock Returns

To measure potential changes in market reactions to PDMR transactions we look at abnormal stock returns. Adhering to the same methodology as used in Lakonishok and Lee (2001), opening and closing prices were used to calculate the intraday returns for the stocks on the day of the publication of a PDMR transaction related to that stock. To the furthest extent possible we wanted to isolate the effect of the PDMR transaction on the intraday stock return to observe the idiosyncratic effect, excluding potential general market and sector-specific effects on that particular date. Hence, in line with Lakonishok and Lee (2001), this was achieved by calculating the abnormal intraday stock return of the stock on the day of the publication of the PDMR transaction. The abnormal stock return was proxied by looking at the delta of the return of the stock itself and the return of the sector index of the stock which provides a good approximation of how the stock would have performed if there were no systematic sentiments related to the general market or the specific sector of the stock during that particular day. Given that the publication of PDMR transactions is not restricted to be publicized only at the times when the stock market is open, there are

frequent occasions of publications happening outside of market opening hours. In such cases, the stock return is instead calculated by looking at the percentage return between the closing price on the preceding trading day and the opening price on the following trading day. This calculation methodology can be summarized in the following equations, where the abnormal stock return, R, is calculated as the percentage change throughout, or between, trading days where P is the price for a given stock x on a given trading day n. In addition, $\hat{x}$ represents the sector index for the given stock and o and c indicates whether it is the closing or opening price of the stock on the trading day.

Abnormal stock returns for PDMR transactions published during market opening hours

$$\boldsymbol{R_{xn}} = \frac{\boldsymbol{P^{c}_{xn} - P^{o}_{xn}}}{\boldsymbol{P^{o}_{xn}}} - \frac{\boldsymbol{P^{c}_{\hat{x}n} - P^{o}_{\hat{x}n}}}{\boldsymbol{P^{o}_{\hat{x}n}}} \qquad (1)$$

Abnormal stock returns for PDMR transactions published before market opening hours

$$\boldsymbol{R_{xn}} = \frac{\boldsymbol{P^{o}_{xn} - P^{c}_{xn-1}}}{\boldsymbol{P^{c}_{xn-1}}} - \frac{\boldsymbol{P^{o}_{\hat{x}n} - P^{c}_{\hat{x}n-1}}}{\boldsymbol{P^{c}_{\hat{x}n-1}}} \qquad (2)$$

Abnormal stock returns for PDMR transactions published after market opening hours

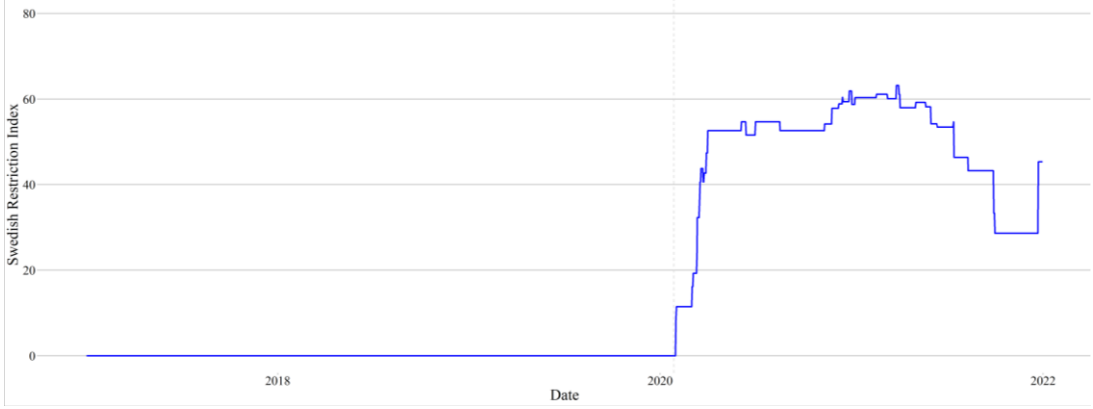
$$\boldsymbol{R_{xn}} = \frac{\boldsymbol{P^{o}_{xn+1} - P^{c}_{xn}}}{\boldsymbol{P^{c}_{xn}}} - \frac{\boldsymbol{P^{o}_{\hat{x}n+1} - P^{c}_{\hat{x}n}}}{\boldsymbol{P^{c}_{\hat{x}n}}} \qquad (3)$$

I. Treatment Variable: Covid-19 Period

In line with Loh and Stulz (2018) the treatment variable that we are studying, is a dummy variable indicating whether the transaction was published during the treatment period or the control period. The treatment period, in this case, is defined as 2020-02-01 until 2021-12-31. This treatment period has been chosen with a similar methodology to Loh and Stulz (2018). They looked at uncertainty during the financial crisis and utilized the Global Economic Policy Uncertainty Index to approximate uncertainty levels to define their treatment period. Given that our crisis was not primarily of financial character, where uncertainty regarding global economic policy is highly relevant, but instead a public health crisis, we looked at the societal restrictions imposed in Sweden as an approximation of uncertainty in society. Societal restrictions can be seen as a proxy for societal uncertainty in a public health crisis given that it indicates a lack of control of the pandemic and its consequences. Despite not adhering to the same index, the same underlying methodology as applied by Loh and Stulz (2018)

has therefore been used, though with a slightly different practical implementation. Societal restrictions related to the Covid-19 pandemic were studied using the "Oxford Covid-19 Government Response Tracker" for Sweden (Oxford University, 2022).

Graph 2. Covid-19 Government Response Tracker - Sweden (2017-2021)



The graph above illustrates the levels of the Swedish Restriction Index in the period 2017-2021. The index uses the societal response of the United Kingdom as the basis which is why the index never reaches 100 for Sweden. This index takes 23 indicators into consideration that are recorded on a scale to reflect the magnitude of the societal reaction to the pandemic. The vertical grey line indicates the split of our control and treatment periods.

(Oxford University, 2022)

The vertical, dashed line in the graph indicates the first time the restriction index was non-zero, which was on 2020-02-01. That was the basis for which the start of the treatment period was chosen. As can be seen in Graph 2, societal restrictions were still broadly implemented throughout 2020 and 2021, with slight deviations, which is the reason 2020-02-01 to 2021-12-31 was chosen. The end of the period was chosen based on data availability, as it was during this time that we began conducting our research on the topic and hence put a hard stop on data collection at this time to avoid sampling bias by having the option to collect additional data to potentially skew the results. The control period on the other hand was defined as 2017-01-01 to 2020-01-31. This period is not symmetrical to the treatment period in the number of days but is instead close to equivalent in the number of PDMR transactions, which is the basis on which the control period was chosen. This was in line with the methodology used by Loh and Stulz (2018) to select their control period. The reason for adhering to the calendar years for the start of the control period and end of the treatment period was to minimize the effect of any potential seasonal trends in the data set, which was then also later controlled for in the regression analysis.

J. Control Variables

In line with the methodology used by Loh and Stulz (2018), we perform a time-series regression to study the effect of the Covid-19 pandemic on the abnormal stock returns following the publication of PDMR transactions. The remaining regression variables are included as control variables to isolate the effect of the treatment variable, while also providing additional insights into the potential correlation between underlying factors in PDMR transactions and their market impact. Loh and Stulz (2018) researched how the impact of changes in equity analyst estimates impacted abnormal stock returns in times of uncertainty compared to normal conditions. In their regression analysis, they included ten control variables in addition to the treatment period dummy variable, with nine of these control variables being related to the equity analyst

recommendation and one being related to the stock itself. Given that we are not researching the exact same topic, even though there are many underlying similarities between the research, we have used other control variables. In our regression model seven control variables were used, and all of them are related to the PDMR transactions, the equivalent of being related to the equity analyst recommendations in our reference. However, it should be mentioned that three of these variables, Trans.Size, Report.Period and Report.Day, is a mixture of information for the PDMR transaction and the stock. Therefore, we consider the model to include both control variables related to the transaction and the underlying transacted stock and hence are aligned with the methodology used by Loh and Stulz (2018).

Variable	Type	Definition
Covid	Treatment	Dummy variable indicating if the PDMR transaction occurred during the treatment period.
Trans. Size	Control	The transaction size of the PDMR trade related to the total number of shares outstanding (non-diluted) of the company, expressed in parts per million (ppm).
Insider. Role	Control	Dummy variable indicating if the insider is the CEO, CFO, or Chairman of the Board in the company.
Incentive. Progr.	Control	Dummy variable indicating if the PDMR transaction was related to an incentive program in the company.
Report. Period	Control	Dummy variable indicating whether the PDMR transaction occurred two weeks after the release of a financial report.
Market. Open	Control	Dummy variable indicating whether the stock exchange was open for trading at the time the PDMR transaction was published.
Report. Day	Control	Dummy variable indicating whether the PDMR transaction was published on the same date as the release of a financial report.
Relative	Control	Dummy variable indicating whether the PDMR transaction was made by a related person to the insider instead of by the insider him-/herself.

The first control variable, Trans.Size, is a numeric variable that specifies the relative size of the transaction in relation to the entire company size. This calculation was based on the number of shares to avoid valuation deviations when calculating the ratio. Hence, the number of shares transacted in the PDMR transaction was divided by the total number of shares outstanding on a non-diluted basis. Given that most transactions are small in relation to the entire company size, this variable was expressed in parts per million (ppm). The second control variable, Insider.Role, is a dummy variable that indicates whether the PDMR that the transaction is related to has a material insider role in the company. A material role has in this case been defined as a CEO, CFO, or Chairman of the Board. In the case that an executive has possessed more than

one role in the company, e.g., being both the CEO and Board member, the more senior, operational role has prevailed in the categorization, i.e., the CEO role in the previous example. This categorization has been made in line with the classification of a material insider role done by Lakonishok and Lee (2001) for PDMRs. This variable is important to include as it is reasonable to assume that the market attributes differing informational value to whether the transaction is made by the CEO or a division manager in the company. The third control variable, Incentive.Progr., is a dummy variable that indicates whether the PDMR transaction was related to an incentive program in the company, i.e., whether the purchase was executed by choice by the executive with his or her own money, or if the transaction was part of the compensation package for that executive. This data was part of the data set from the SFSA and is self-reported by the PDMR when registering the transaction. The fourth control variable, Report.Period, indicates whether the transaction was made within 14 days after the release of a financial report. The information on reporting dates was extracted from Refinitiv. This variable is important to consider as this indicates the period when the informational gap between the PDMRs and investors is the lowest, given financial information has recently been released, which can be assumed to impact the informational value attributed to the PDMR transaction. The fifth control variable, Market.Open, is a dummy variable that indicates whether the PDMR transaction was published at a time when the market was open. Given that there are no restrictions on when a PDMR can self-report their transactions, PDMR transactions can be published both before and after market opening hours, as well as during the weekend and bank holidays, which this variable includes in the model. This is important to include in the regression model as a publication of a transaction outside of market opening hours, makes it more difficult to attribute the potential abnormal market return to the PDMR transaction. The sixth control variable, Report.Day, is a dummy variable that indicates whether the PDMR transaction was made on the same date as a financial report was published. This is important to isolate as the reaction of the market on said date can be assumed to relate to the financial report rather than the PDMR transaction, which is important to be able to isolate. The final control variable, Relative, is a dummy variable that indicates whether the transaction was executed by a person in close relation to the PDMR rather than the insider him-/herself. According to the Swedish Market Abuse Regulation ("MAR"), a person in close relation to a PDMR is defined as a spouse, or a partner equivalent to a spouse, a dependent child, a relative sharing the same household, and certain other exceptions (SFSA, 2022). This data is self-reported by the PDMR and included in the data set from the SFSA. This is an important aspect to consider in the regression model as the market may attribute different informational values to the transaction depending on if it was executed by the PDMR or a relative to the PDMR.

The purpose of including the specified control variables was to control for the relevant differences in these factors between the control and treatment period. These differences can be seen in the detailed descriptive statistics (Appendix C). Given these changes between the periods, there would be a risk that they would distort the outcome if omitted from the regression model and in turn lower the accuracy of our findings, which is why they were instead included as control

variables.

Below follows the descriptive statistics for the dummy and numeric variables, split between PDMR purchase and sales transactions.

Table 4a. Descriptive Statistics Independent Variables - PDMR Purchases

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Covid-19	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
Yes	10,980	*48%*	2,702	*41%*	1,874	*44%*	979	*44%*	5,425	*54%*
No	12,089	*52%*	3,943	*59%*	2,339	*56%*	1,231	*56%*	4,576	*46%*
Sector	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
Automobiles and Parts	209	*1%*	39	*1%*	124	*3%*	-	-	46	*0%*
Banks	491	*2%*	270	*4%*	221	*5%*	-	-	-	-
Basic Resources	698	*3%*	362	*5%*	80	*2%*	81	*4%*	175	*2%*
Chemicals	326	*1%*	-	-	-	-	-	-	326	*3%*
Construction and Materials	2,757	*12%*	1,463	*22%*	225	*5%*	321	*15%*	748	*7%*
Consumer Products and Services	1,015	*4%*	122	*2%*	348	*8%*	143	*6%*	402	*4%*
Energy	365	*2%*	24	*0%*	23	*1%*	9	*0%*	309	*3%*
Financial Services	663	*3%*	117	*2%*	273	*6%*	7	*0%*	266	*3%*
Food, Beverage and Tobacco	323	*1%*	2	*0%*	220	*5%*	-	-	101	*1%*
Health Care	3,833	*17%*	345	*5%*	859	*20%*	510	*23%*	2,119	*21%*
Household & Personal Products	34	*0%*	-	-	-	-	34	*2%*	-	-
Industrial Goods and Services	4,291	*19%*	1,730	*26%*	788	*19%*	357	*16%*	1,416	*14%*
Media	181	*1%*	-	-	80	*2%*	1	*0%*	100	*1%*
Personal Care, Drug and Grocery Stores	164	*1%*	33	*0%*	40	*1%*	-	-	91	*1%*
Real Estate	1,587	*7%*	767	*12%*	365	*9%*	-	-	455	*5%*
Retail	889	*4%*	394	*6%*	140	*3%*	1	*0%*	354	*4%*
Technology	3,510	*15%*	331	*5%*	223	*5%*	497	*22%*	2,459	*25%*
Telecommunications	1,142	*5%*	621	*9%*	32	*1%*	102	*5%*	387	*4%*
Travel and Leisure	545	*2%*	25	*0%*	172	*4%*	133	*6%*	215	*2%*
Utilities	46	*0%*	-	-	-	-	14	*1%*	32	*0%*
Insider Role	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
Non-material	15,853	*69%*	5,251	*79%*	2,823	*67%*	1,334	*60%*	6,445	*64%*
Material	7,216	*31%*	1,394	*21%*	1,390	*33%*	876	*40%*	3,556	*36%*
Report Period	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
No	17,423	*76%*	5,012	*75%*	2,932	*70%*	1,595	*72%*	7,884	*79%*
Yes	5,646	*24%*	1,633	*25%*	1,281	*30%*	615	*28%*	2,117	*21%*
Market Open	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
Closed	6,570	*28%*	1,720	*26%*	1,184	*28%*	678	*31%*	2,988	*30%*
Open	16,499	*72%*	4,925	*74%*	3,029	*72%*	1,532	*69%*	7,013	*70%*
Report Day	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
No	22,653	*98%*	6,534	*98%*	4,116	*98%*	2,154	*97%*	9,849	*98%*
Yes	416	*2%*	111	*2%*	97	*2%*	56	*3%*	152	*2%*
Relative	**23,069**	***100%***	**6,645**	***100%***	**4,213**	***100%***	**2,210**	***100%***	**10,001**	***100%***
No	16,832	*73%*	5,058	*76%*	3,301	*78%*	1,701	*77%*	6,772	*68%*
Yes	6,237	*27%*	1,587	*24%*	912	*22%*	509	*23%*	3,229	*32%*

The table above represents descriptive statistics across Stock Exchange Lists for the independent dummy variables covering PDMR purchase transactions, covering in total 23,069 purchase transactions. "-" indicates that there is no transaction for that particular combination of variables.

Table 5a. Descriptive Statistics Independent Variable: Trans.Size - PDMR Purchases

Stock Exchange List	N	Mean	Median	Std. Dev.	Min	Max
All	**23,069**	**10 ppm**	**0.10 ppm**	**42 ppm**	**~ 0 ppm**	**7,205 ppm**
Large Cap	6,645	8 ppm	0.01 ppm	55 ppm	~ 0 ppm	1,412 ppm
Mid Cap	4,213	2 ppm	0.07 ppm	23 ppm	~ 0 ppm	1,118 ppm
Small Cap	2,210	4 ppm	0.17 ppm	31 ppm	~ 0 ppm	797 ppm
First North	10,001	17 ppm	0.22 ppm	63 ppm	~ 0 ppm	7,205 ppm

The table above shows the descriptive statistics for the independent variable Trans.Size on each stock exchange list and on an aggregated level for PDMR purchase transactions. Transaction size is calculated as the transaction size, in shares, in relation to the company's total number of shares outstanding, expressed in parts per million (ppm = 0.0001%). The data is comprised of 23,069 purchase transactions across all stock exchange lists.

Table 4b. Descriptive Statistics Independent Variables - PDMR Sales

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Covid-19	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
Yes	4,032	*49%*	1,124	*51%*	732	*41%*	273	*38%*	1,903	*55%*
No	4,139	*51%*	1,080	*49%*	1,065	*59%*	441	*62%*	1,553	*45%*
Sector	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
Automobiles and Parts	22	*0%*	1	*0%*	17	*1%*	-	-	4	*0%*
Banks	172	*2%*	155	*7%*	17	*1%*	-	-	-	-
Basic Resources	238	*3%*	135	*6%*	4	*0%*	32	*4%*	67	*2%*
Chemicals	105	*1%*	-	-	-	-	-	-	105	*3%*
Construction and Materials	349	*4%*	195	*9%*	110	*6%*	29	*4%*	15	*0%*
Consumer Products and Services	635	*8%*	136	*6%*	119	*7%*	82	*11%*	298	*9%*
Energy	297	*4%*	24	*1%*	7	*0%*	28	*4%*	238	*7%*
Financial Services	223	*3%*	79	*4%*	81	*5%*	4	*1%*	59	*2%*
Food, Beverage and Tobacco	126	*2%*	35	*2%*	54	*3%*	-	-	37	*1%*
Health Care	1,297	*16%*	153	*7%*	658	*37%*	51	*7%*	435	*13%*
Industrial Goods and Services	1,898	*23%*	471	*21%*	331	*18%*	153	*21%*	943	*27%*
Media	45	*1%*	-	-	13	*1%*	3	*0%*	29	*1%*
Personal Care, Drug and Grocery Stores	133	*2%*	8	*0%*	4	*0%*	-	-	121	*4%*
Real Estate	359	*4%*	208	*9%*	109	*6%*	-	-	42	*1%*
Retail	333	*4%*	139	*6%*	61	*3%*	1	*0%*	132	*4%*
Technology	1,269	*16%*	94	*4%*	146	*8%*	260	*36%*	769	*22%*
Telecommunications	468	*6%*	340	*15%*	4	*0%*	18	*3%*	106	*3%*
Travel and Leisure	161	*2%*	31	*1%*	62	*3%*	49	*7%*	19	*1%*
Utilities	41	*1%*	-	-	-	-	4	*1%*	37	*1%*
Insider Role	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
Non-material	5,965	*73%*	1,825	*83%*	1,159	*64%*	506	*71%*	2,475	*72%*
Material	2,206	*27%*	379	*17%*	638	*36%*	208	*29%*	981	*28%*
Report Period	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
No	6,422	*79%*	1,784	*81%*	1,128	*63%*	596	*83%*	2,914	*84%*
Yes	1,749	*21%*	420	*19%*	669	*37%*	118	*17%*	542	*16%*
Market Open	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
Closed	2,973	*36%*	672	*30%*	574	*32%*	344	*48%*	1,383	*40%*
Open	5,198	*64%*	1,532	*70%*	1,223	*68%*	370	*52%*	2,073	*60%*
Report Day	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
No	8,118	*99%*	2,193	*100%*	1,779	*99%*	711	*100%*	3,435	*99%*
Yes	53	*1%*	11	*0%*	18	*1%*	3	*0%*	21	*1%*
Relative	**8,171**	***100%***	**2,204**	***100%***	**1,797**	***100%***	**714**	***100%***	**3,456**	***100%***
No	5,415	*66%*	1,767	*80%*	1,402	*78%*	471	*66%*	1,775	*51%*
Yes	2,756	*34%*	437	*20%*	395	*22%*	243	*34%*	1,681	*49%*

The table above represents descriptive statistics across Stock Exchange Lists for the independent dummy variables covering PDMR purchase transactions, covering in total 8,171 sales transactions. "-" indicates that there is no transaction for that particular combination of variables.

Table 5b. Descriptive Statistics Independent Variable: Trans.Size - PDMR Sales

Stock Exchange List	N	Mean	Median	Std. Dev.	Min	Max
All	**8,171**	**9 ppm**	**0.16 ppm**	**62 ppm**	**~ 0 ppm**	**2,415 ppm**
Large Cap	2,204	15 ppm	0.03 ppm	110 ppm	~ 0 ppm	2,415 ppm
Mid Cap	1,797	4 ppm	0.12 ppm	23 ppm	~ 0 ppm	474 ppm
Small Cap	714	8 ppm	0.40 ppm	34 ppm	~ 0 ppm	450 ppm
First North	3,456	7 ppm	0.29 ppm	31 ppm	~ 0 ppm	592 ppm

The table above shows the descriptive statistics for the independent variable Trans.Size on each stock exchange list and on an aggregated level for PDMR sales transactions. Transaction size is calculated as the transaction size, in shares, in relation to the company's total number of shares outstanding, expressed in parts per million (ppm = 0.0001%). The data is comprised of 8,171 sales transactions across all stock exchange lists.

Table 6. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	VIF Purchases	VIF Sales
(1) Covid-19 - Yes	1.000								1.0186	1.0446
(2) Transaction Size of Company (%)	0.001	1.000							1.0007	1.0241
(3) High-ranking Insider - Yes	**0.052*** **	0.011	1.000						1.0283	1.0347
(4) Incentive Program Related - Yes	**-0.061*** **	**0.015***	**-0.092*** **	1.000					1.0502	1.0908
(5) Transaction in Reporting Period - Yes	0.005	-0.006	**0.041*** **	**-0.039*** **	1.000				1.0642	1.0597
(6) Market Open on Publication - Yes	**-0.024*** **	0.005	0.011	**0.080*** **	-0.012	1.000			1.0073	1.0306
(7) Publication on Reporting Date - Yes	**0.017****	-0.001	**0.018****	**-0.033*** **	**0.222*** **	**0.025*** **	1.000		1.0644	1.0267
(8) Transaction by Relative - Yes	**0.061*** **	0.006	**-0.040*** **	**-0.170*** **	**-0.054*** **	-0.011	**-0.038*** **	1.000	1.0362	1.0849

The table showcases the results of The Pearson Product-Moment Correlation two-tailed tests of each combination of independent variables in the regression models. Given that the regression models are split between transaction types, the VIF-values for the Purchase and Sales regression models are presented separately. Bold values indicate statistical significance at α<0.1.
*** p-value<0.01, **p-value<0.05, *p-value<0.1

We perform a multicollinearity test on the independent variables of the regression variables by calculating the Variance Inflation Factors (VIF). None of the independent variables have a VIF value that supersedes the standard limit of 10, meaning that we can conclude that multicollinearity between independent variables is not a material problem for our regression model (Newbold, 2013). The correlation matrix is performed on the entire data set regardless of transaction type, while the VIF is calculated separately for PDMR purchases and sales given that this is calculated on an individual regression model that differs between the transaction types.

In addition to this multicollinearity test, we also run an additional multicollinearity test across a total of 50 variables to check for correlation between fixed effect variables such as sector, stock exchange list, publication day, publication month, and detailed insider roles. This multicollinearity test can be found in Appendix D. This was done with the purpose to test for omitted variable bias, given that they could reveal potential fixed effects that are not captured by the linear regression model. Given that we found no relevant correlation between these additional control variables and the treatment variable, and that the VIF values were well within the standard limit, we can conclude that the risk for omitted variable bias for these defined additional control variables is low.

K. Placebo Variable

To conduct a robustness test of our empirical results, testing for potential overarching time trends in the data that were not related to the exogenous change in uncertainty, we also created a placebo variable to run a placebo test. The rationale and method behind this decision are described in detail in the methodology. To run the placebo test we had to create a placebo variable, to test for potential time trends.

Variable	Definition
Placebo	Dummy variable indicating if the PDMR transaction occurred during the placebo period (2018-09-08 to 2020-01-31) or if it occurred in the non-placebo period (2017-01-01 – 2018-09-07) in the control data.

This was done by splitting the control period data in half in terms of the number of transactions, all while maintaining the chronological order of the data. The control period data that stretched from 2017-01-01 to 2020-01-31, was therefore split on the 8th of September 2018 (which was the date that generated the most even distribution of transactions between the two halves of the data set). All transactions that occurred before said date was given a 0 in the placebo variable, while all transaction that occurred after this date was given a 1 in the

placebo variable. This focus on splitting the data set on the number of transactions instead of on the number of days was in line with the methodology used by Loh and Stulz (2018).

Below follows the descriptive statistics for the placebo variable used in the placebo test, split between PDMR purchase and sales transactions.

Table 7a. Descriptive Statistics Placebo Variable - PDMR Purchases

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Placebo	**12,089**	***100%***	**3,943**	***100%***	**2,339**	***100%***	**1,231**	***100%***	**4,576**	***100%***
Yes	6,042	*50%*	2,103	*53%*	1,219	*52%*	652	*53%*	2,068	*45%*
No	6,047	*50%*	1,840	*47%*	1,120	*48%*	579	*47%*	2,508	*55%*

The table above represents descriptive statistics across Stock Exchange Lists for the placebo variable in the control peroid covering PDMR purchase transactions, covering in total 12,089 purchase transactions. "-" indicates that there is no transaction for that particular combination of variables.

Table 7b. Descriptive Statistics Placebo Variable - PDMR Sales

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Placebo	**4,139**	***100%***	**1,080**	***100%***	**1,065**	***100%***	**441**	***100%***	**1,553**	***100%***
Yes	2,084	*50%*	632	*59%*	447	*42%*	269	*61%*	736	*47%*
No	2,055	*50%*	448	*41%*	618	*58%*	172	*39%*	817	*53%*

The table above represents descriptive statistics across Stock Exchange Lists for the placebo variable in the control peroid covering PDMR sales transactions, covering in total 4,139 purchase transactions. "-" indicates that there is no transaction for that particular combination of variables.

Methodology

A. General Methodology

Though our study has been heavily influenced by the research conducted by Lakonishok and Lee (2001), given its connection to the informational value of PDMR transactions, our research question is formed in such a way that the methodology used by these researchers would not be appropriate to use to derive an accurate conclusion. That is since we are trying to examine the difference in informational value between periods of different market sentiments, which cannot be done by replicating the methodology used by Lakonishok and Lee (2001). For this purpose, the methodology used by Loh and Stulz (2018) is instead replicated, motivated by the strong underlying similarities in the research as discussed in the introduction. Instead of looking at the abnormal stock returns in conjunction with revised analyst recommendations between periods of differing market sentiment, we will be looking at the abnormal stock returns in conjunction with PDMR trades during the Covid-19 crisis compared with normal market conditions. This type of analysis can either be studied directly through a comparison of the dependent variable between the treatment and control period or through a time-series regression. In line with Loh and Stulz (2018), both methods will be used in this study to be able to determine whether there is a significant difference between the abnormal returns in the control and treatment period and to determine whether such a difference derives from the change in uncertainty or if it is due to other changes in the independent variables.

As stated in the Data Section, the ideal methodology would be to randomly assign an uncertainty to homogenous firms equally spread in all sectors and then study the two groups over time to see if there is an endogenous effect on abnormal stock returns following the introduction of the exogenous change in uncertainty. However, that is a hypothetical approach that is not feasible in reality. Instead,

we have had to use observational data from a global public health crisis as a proxy for market uncertainty and compare the abnormal stock returns following PDMR transactions to the equivalent returns in the control period. This approach differs from the ideal scenario as it suffers from possible time trends, omitted variable bias, and problems with sector comparability that limits the accuracy of the results that we derive. Our research methodology has been constructed to reduce and test the extent of such limitations. However, attaining a methodology that eradicates all possible limitations would not be achievable. Hence, the limitations that prevail are discussed in detail to inform the reader of their potential implications on the results.

B. Statistical T-tests

In line with Loh and Stulz (2018), our direct study through comparison between the control and treatment period is executed using Welch's t-tests for unequal variances. This statistical test is used to determine whether the equally weighted means of the abnormal stock returns following the announcement of PDMR transactions are significantly different between times of extreme uncertainty (approx. Q1 2020 to Q4 2021) and normal market conditions (approx. Q1 2017 to Q4 2019). The analysis is conducted by calculating the test statistic, using equation 4, and then analyzing the level of significance by which the null hypothesis can be rejected by observing the p-value associated with each t-test. The formula through which one calculates the test statistic is given by Newbold et al (2013) and compares the sample mean of the treatment period ($\bar{x}$) with the sample mean of the control period ($\bar{y}$), with s representing the sample variance and n the sample size:

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \tag{4}$$

Initially, the analysis is meant to test if the average abnormal return following the publication of a PDMR transaction differs in times of uncertainty. This is done by dividing the data into two subsets, depending on if the transaction type is classified as a purchase or a sales transaction. Since the characteristics of the effect of the transaction types are expected to neutralize the results when looking at the entire data set, we instead want to look at one-sided Welch's t-tests split between the different transaction types. As stated in the Hypotheses Section ,we would expect that both types of PDMR transactions would generate a more extreme abnormal share return following the announcement. This would manifest itself as a more negative abnormal return for sales and a more positive abnormal return for purchases. Given this view, the following null and alternative hypotheses have been set up for the different transaction types. $\bar{R}$ representing abnormal returns, with the superscript b and s representing the buying and selling transaction type respectively, and the subscript c and t representing the control and treatment period respectively.

Purchase PDMR transactions

$$H_0: \bar{R}_t^b - \bar{R}_c^b \leq 0$$
$$H_1: \bar{R}_t^b - \bar{R}_c^b > 0 \quad (5)$$

Sales PDMR transactions

$$H_0: \bar{R}_t^s - \bar{R}_c^s \geq 0$$
$$H_1: \bar{R}_t^s - \bar{R}_c^s < 0 \quad (6)$$

Additionally, we perform t-tests on the average abnormal returns for the different sectors represented in our data set. This is done with the intuition that the degree of uncertainty should differ between industries, given the inherent diversity of operational challenges and opportunities that the Covid-19 crisis posed. As noted from the S&P report, there is a discrepancy between how e.g., the Travel and Leisure industry and the Health Care industry were impacted by the pandemic, as well as their default risk, which should be reflected in how the market reacts to PDMR transactions within these different industries (Standard & Poor's, 2022). Given that these effects are more ambiguous than on the aggregate level, this analysis will be performed as a two-sided Welch's t-tests, given potentially varying directional effects among industries. The following null and alternative hypotheses have been set up for the sector-level analysis with this in mind:

$$H_0: \bar{R}_t - \bar{R}_c = 0$$
$$H_1: \bar{R}_t - \bar{R}_c \neq 0 \quad (7)$$

C. Time-series Regression

In line with the methodology used by Loh and Stulz (2018), we also perform a time-series regression analysis to try to isolate the effect of the treatment period by investigating the time-series determinants related to each dependent variable, and their statistical significance. The independent variables that were presented in the Data Section are used for the time-series regressions.

Following the methodology of Loh and Stulz (2018), the regression is conducted as an ordinary least squared (OLS) linear regression, to determine the relationship between the dependent variable and the independent variables, both on the individual stock exchange lists and at an aggregated level. In line with the method logic introduced in the Data Section, the linear regressions are split between purchase and sales transactions to avoid neutralizing the effect of the PDMR trade announcement. The model behind the linear regression can be expressed in the following way:

$$R = \beta_0 + \beta_1 Covid + \beta_2 Trans.Size + \beta_3 Insider.Role + \beta_4 Incentive.Progr. + \beta_5 Report.Period + \beta_6 Market.Open + \beta_7 Report.Day + \beta_8 Relative + \varepsilon \quad (8)$$

D. Placebo Test

In addition to the t-tests and time-series regression, we have also decided to include a placebo test as a robustness test of our results. This contrasts with Loh and Stulz (2018) that did not have such a test in their research. That has to do with the fact that they included data with uncertain market conditions from multiple, separate time periods and therefore were not as exposed to time trends. However, given that we are looking at a period of long, continuous uncertainty and contrasting this with a long, continuous control period that in its entirety occurred before the treatment period, the outcome of our method runs the risk of capturing general trends that develop in the markets over time. To test if our results derive from the behavioral changes following an increase in market uncertainty or are due to noise in the market data, we perform a robustness test in the form of this placebo test.

A placebo test is a statistical method used to diagnose problems with research designs in observational studies, whereby a research method is applied to a data set that should not yield any significant results for the placebo variable. This is done to test whether the research method accurately identifies correlations in the data or simply reacts to noise (Eggers et al, 2021). For our study, we use our linear regression model, which was described in the previous section, and apply it to our control period data. We then run the same regression model as previously described, with the only difference that it is run solely on the control period data and that the treatment variable is changed to the placebo period variable (Placebo) instead of the uncertainty period variable (Covid). The model used for the Placebo Test can therefore be described in the following way:

$$\begin{aligned} \boldsymbol{R = \beta_0 + \beta_1 Placebo + \beta_2 Trans.Size + \beta_3 Insider.Role +} \\ \boldsymbol{\beta_4 Incentive.Progr. + \beta_5 Report.Period +} \\ \boldsymbol{\beta_6 Market.Open + \beta_7 Report.Day + \beta_8 Relative + \varepsilon} \end{aligned} \quad (9)$$

In line with the rest of our methodology and the research done by Loh and Stulz (2018), we run the placebo test separately for PDMR purchase and sales transactions to determine whether the research method is inherently flawed due to non-controlled time trends.

Empirical Results

A. Statistical T-tests

Table 8 presents the results from the t-tests on changes in average abnormal stock returns between the control period and the treatment period. This test includes all available transactions in both the control and treatment period without controlling for industry, though with a split between purchase and sales PDMR transactions, in line with the reasoning presented in the methodology. Looking at changes in the average abnormal stock return between the periods, we can conclude that across all stock exchange lists the average abnormal stock return for PDMR purchase transactions increased by 0.39% during the treatment period. This outcome is in line with our hypothesis that the abnormal stock return would increase during the treatment period. This result is statistically significant at the 1% significance level and was consistent across all stock

exchange lists. Stocks on First North saw the largest change in abnormal stock returns, with an average increase of 0.48% in conjunction with PDMR purchases, with the value being significant at 1%. Transactions on the Large Cap and Mid Cap lists also experienced slightly smaller increases at the 1% significance level. Returns related to PDMR transactions on Small Cap stocks were not shown to be statistically significant.

Table 8. Transaction Type T-Test Results

	Change in Return	
Stock Exchange List	Purchases	Sales
All	**0.39%*** **	(0.04)%
Large Cap	**0.16%*** **	**(0.26)%*** **
Mid Cap	**0.30%*** **	0.82%
Small Cap	0.11%	0.19%
First North	**0.48%*** **	**(0.34)%***

The table reports the difference in average returns between the control and treatment period, split by transaction type and company size. A positive value indicates an increase in the average return in the treatment period compared to the control period, and vice versa. The returns are calculated as a percentage price change. The data covers the price reaction of 31,240 PDMR transactions, see descriptive statistics for the division of data between company sizes and transaction types. The one-sided Welch's t-tests have been conducted by comparing the PDMR transactions in the treatment period with the PDMR transactons in the control period, grouped by company sizes. Bold values indicate statistical significance at $\alpha<0.1$.
*** p-value<0.01, ** p-value<0.05, * p-value<0.1

Looking at the equivalent results for PDMR sales transactions, no statistically significant results were derived when looking at securities across all lists, contrary to our hypothesis. Large Cap stocks saw the largest change in the negative effect from PDMR sales when comparing the period, a result that was significant at the 1% significance level, with First North having a larger negative effect but at the 10% significance level. No other individual stock exchange list had any significant changes in the abnormal stock returns between the two periods, though worth highlighting that Mid and Small Cap had a positive change in their abnormal returns, though lacking statistical significance.

In Table 9a results of the t-tests split by sector for PDMR purchase transactions are showcased. On the aggregate level, approximately half of the sectors have some sort of significant results, with 'Banks', 'Automobiles and Parts' and 'Personal Care, Drug and Grocery Stores' showing the highest increases in abnormal share returns between the control and treatment period, at 1%, 5% and 5% significance level respectively. For 'Banks' this change is mainly prevalent across the two largest stock exchange lists where results are 1.10% at significance level 5% and 1.37% at significance level 5% for Large Cap and Mid Cap respectively. These results are in line with our hypothesis that there would be heterogeneity between different sectors in market reaction. Furthermore, in line with our hypothesis 'Automobiles and Parts' saw a significant increase in abnormal stock returns in the treatment period. However, we did not see the same results for 'Energy' and 'Travel and Leisure', which we expected. In addition, 'Food, Beverage and Tobacco', 'Basic Resources', 'Consumer Products and Services' and 'Retail' all showcase an increase in abnormal stock returns of more than half a percent between the periods at a significance level of 1%.

Two sectors showcase surprising results in the form of statistically significant opposite effects between different stock exchange lists. The first one of these industries is 'Technology' which has an increase of 1.09% on average on Large Cap and a decrease of -1.15% on Small-Cap between the periods, both being at the 1% significance level. The other sector is 'Health Care' with a negative effect

of the average abnormal stock return during the Covid-19 crisis of -0.74% on Large Cap and an equivalent positive effect of 1.20% on Small Cap, both being at the 1% significance level.

One industry that stands out is 'Travel and Leisure' which showcases a clear decline of the abnormal stock return during the Covid-19 crisis, contrary to our hypothesis, at a 1% significance level at the aggregate level. Even though this negative impact can be seen across most stock exchange lists, the effect seems to mainly be derived from the companies within the sector that are listed on First North, where the decline is both large in its effect and statistically significant at the 1% level. For the remaining sectors the effects are both small and statistically insignificant on the aggregate stock exchange list level, and hence point toward a very limited sector-specific impact on the abnormal stock returns.

Table 9a. Sector T-Test Results for PDMR Purchases

	Stock Exchange List				
Sector	All	Large Cap	Mid Cap	Small Cap	First North
Automobiles and Parts	**1.29%****	-	**1.03%****	-	**3.98%****
Banks	**1.90%*****	**1.10%****	**1.37%****	-	-
Basic Resources	**0.81%*****	**0.72%*****	-0.46%	-0.29%	0.87%
Chemicals	0.31%	-	-	-	0.31%
Construction and Materials	0.08%	**-0.22%*****	-0.39%	**-0.92%*****	**1.20%*****
Consumer Products and Services	**0.78%*****	0.08%	**0.52%****	0.13%	0.73%
Energy	**1.24%****	-0.24%	**-1.05%****	3.48%	**1.38%****
Financial Services	0.03%	-0.44%	0.24%	-	-0.17%
Food, Beverage and Tobacco	**0.79%*****	-	**0.95%*****	-	-0.34%
Health Care	0.13%	**-0.74%*****	-0.10%	**1.20%*****	-0.03%
Industrial Goods and Services	**0.50%*****	0.08%	-	-0.39%	**1.42%*****
Media	1.02%	-	-0.17%	-	1.88%
Personal Care, Drug and Grocery Stores	**1.33%****	1.08%	-0.73%	-	-
Real Estate	**0.31%****	0.01%	**0.41%****	-	**1.37%*****
Retail	**0.71%*****	0.10%	0.59%	-	0.51%
Technology	-0.06%	**1.09%*****	1.03%	**-1.15%*****	-0.06%
Telecommunications	0.35%	0.06%	-1.33%	-0.52%	1.42%
Travel and Leisure	**-0.98%*****	-2.17%	0.22%	-0.48%	**-2.33%*****
Utilities	3.51%	-	-	-	**4.41%***

The table reports the difference in average returns between the control and treatment period, split by sector and company size. A positive value indicates an increase in the average return in the treatment period compared to the control period, and vice versa. The returns are calculated as a percentage price change. The data covers the price reaction of 31,240 PDMR transactions, see summary statistics for the division of data between sectors and company sizes. The two-sided Welch's t-tests have been conducted by comparing the PDMR purchase transactions in the treatment period with the PDMR purchase transactons in the control period, grouped by sector and company sizes. Bold values indicate statistical significance at $\alpha<0.1$. "-" indicate that it was not possible to conduct a t-test due to insufficient quantities of data.

In Table 9b results of the t-tests split by industries for PDMR sales transactions are showcased. On the aggregate market level, there are slightly fewer sectors with significant results. The largest decreases in average abnormal stock returns between the periods can be seen among the 'Financial Services', 'Industrial Goods and Services' and 'Technology' industries that have an effect of -1.01%, -0.73%, and -0.65% at 5%, 1%, and 5% significance level respectively. For the two latter sectors, this effect can be seen across the stock exchange lists, but significant results only exist on Large and Small Cap for 'Financial Services'. 'Food Beverage and Tobacco', 'Utilities' and 'Telecommunications' also stand out in these results given that they have an increase in the average abnormal stock return related to PDMR sales transactions between the periods, which are both significant at the 5% level. For the two former industries, this effect seems to be derived from First North securities, with a large positive effect at 5% significance, while the driver of the 'Telecommunications' is more ambiguous. These results also showcase heterogeneity among different industries in market

reaction, in line with our hypothesis.

When comparing Tables 9a and 9b for significant results on the aggregate stock exchange list level, it is evident that a large, statistically significant positive effect on PDMR purchases during the Covid-19 crisis rarely has an equivalent negative effect on PDMR sales. This is contrary to our hypothesis given that we thought that the abnormal stock return would be dependent solely on industry rather than transaction type, and hence implicitly thought that there would be symmetry in the results, which was not the case. It is only 'Industrial Goods and Services' that has significant symmetrical effects for both PDMR purchases and sales, while other industries seem to have asymmetrical effects between the different transaction types.

Table 9b. Sector T-Test Results for PDMR Sales

	Stock Exchange List				
Sector	All	Large Cap	Mid Cap	Small Cap	First North
Automobiles and Parts	-	-	-	-	-
Banks	0.30%	0.05%	3.14%	-	-
Basic Resources	0.09%	**-0.49%***	0.60%	-1.84%	1.40%
Chemicals	0.81%	-	-	-	0.81%
Construction and Materials	-0.11%	**0.46%****	-0.51%	**-0.79%***	-3.18%
Consumer Products and Services	-0.34%	0.06%	**2.26%*****	**-2.97%***	-1.41%
Energy	-0.59%	-	0.90%	0.66%	-0.71%
Financial Services	**-1.01%****	**-1.67%***	-0.14%	**-5.10%***	-1.95%
Food, Beverage and Tobacco	**0.94%****	-0.11%	-0.25%	-	**2.76%****
Health Care	-0.10%	**-0.91%****	**1.00%*****	-0.01%	**-1.95%*****
Industrial Goods and Services	**-0.73%*****	**-0.43%*****	-0.29%	**2.48%*****	**-1.31%*****
Media	1.57%	-	-1.73%	-	3.88%
Personal Care, Drug and Grocery Stores	-0.51%	-	-	-	**-0.91%****
Real Estate	0.04%	-0.07%	0.11%	-	0.62%
Retail	0.07%	0.49%	-0.16%	-	-0.13%
Technology	**-0.65%****	**1.73%****	**-0.75%***	-0.44%	**-1.09%*****
Telecommunications	**2.58%****	**-1.06%*****	-	1.46%	-
Travel and Leisure	-0.08%	0.23%	0.43%	-0.37%	1.43%
Utilities	**4.61%****	-	-	-	**4.46%****

The table reports the difference in average returns between the control and treatment period, split by sector and company size. A positive value indicates an increase in the average return in the treatment period compared to the control period, and vice versa. The returns are calculated as a percentage price change. The data covers the price reaction of 31,240 PDMR transactions, see summary statistics for the division of data between sectors and company sizes. The two-sided Welch's t-tests have been conducted by comparing the PDMR sales transactions in the treatment period with the PDMR sales transactons in the control period, grouped by sector and company sizes. Bold values indicate statistical significance at α<0.1. "-" indicate that it was not possible to conduct a t-test due to insufficient quantities of data.
*** p-value<0.01, ** p-value<0.05, * p-value<0.1

B. Time-series Regression

Table 10a shows the outcome of the regression on abnormal stock returns for the PDMR purchase transactions. When looking at the effect of the treatment period, the results are very much in line with that of the t-tests, i.e., that there is a statistically significant positive effect on the abnormal stock returns during the Covid-19 crisis on the aggregate market level. Given that the linear regression method also considers the effects of other independent variables, the effect seen by the treatment variable can be considered more isolated than that of the t-tests. Important to note however is that the regression method only indicates a correlation between dependent and independent variables, not causality. Looking across the stock exchange lists, the effect is prevalent throughout, though only statistically significant for Large Cap, Mid Cap, and First North at 5%, 5%, and 1% significance levels respectively. The effect is most prominent for First North. These results are also broadly in line with those presented from Welch's t-test. This is in line with our hypothesis that smaller

lists would have larger effects on PDMR transactions during uncertain times. Another noteworthy aspect of these results is that almost all the independent variables included in our regression model have a statistically significant explanatory value on the aggregate level.

The largest positive effects on abnormal stock returns can be derived from whether the transaction is associated with a high-ranking PDMR (CEO, CFO, or Chairman) and if the transaction was published 14 days after the release of a financial report. Furthermore, multiple statistically significant negative effects can also be found in the regression model on the aggregate market level, with transactions related to incentive programs decreasing the abnormal stock returns following the trade announcement. Furthermore, the publication of the PDMR transaction on the same date as a financial report has the largest negative effect on abnormal stock returns. However, this should be seen in the light that increased market activity and changes to investor sentiment are to be expected on such a day given the release of new financial information in the report. The only independent variable that lacks any relevant statistical significance, both on the individual stock exchange level and at the aggregate, is the size of PDMR transactions in relation to the company size. Our regression indicates that there is no correlation between the size of the PDMR transaction and the abnormal stock returns.

When looking at the individual stock exchange level the statistical significance of the coefficient of the independent variables is generally not as extensive. Being a high-ranking PDMR, publishing the transaction on the date of a financial report or the 14 days following the release of a financial report seem to have statistically significant effects across a majority of the stock exchange lists. Worth noting here is that transactions related to stocks on the Small Cap list seem to have deviating factors with statistically significant effects. However, this might have to do with the lower sample size of Small Cap transactions compared to the other stock exchange lists.

Table 10a. Regression Results for PDMR Purchase Transactions

Dependent Variable: Abnormal Stock Return					
	Stock Exchange List				
	All	Large Cap	Mid Cap	Small Cap	First North
Covid-19 - Yes	**0.3%*** **	**0.1%** **	**0.3%** **	0.2%	**0.4%*** **
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Transaction Size of Company (%)	0.0%	0.0%	-0.0%	**-0.0%***	0.0%
	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)
High-ranking Insider - Yes	**0.5%*** **	**0.3%*** **	**0.4%*** **	**0.4%** **	**0.5%*** **
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Incentive Program Related - Yes	**-0.3%*** **	-0.0%	-0.1%	**-0.9%** **	-0.2%
	(0.1%)	(0.1%)	(0.2%)	(0.4%)	(0.3%)
Transaction in Reporting Period - Yes	**0.3%*** **	**-0.2%*** **	**0.6%*** **	0.2%	**0.6%*** **
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Market Open on Publication - Yes	**0.1%***	**-0.1%** **	-0.1%	**0.5%** **	**0.2%** **
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Publication on Reporting Date - Yes	**-1.1%*** **	**-0.6%*** **	**-1.7%*** **	-0.3%	**-1.5%*** **
	(0.2%)	(0.2%)	(0.3%)	(0.6%)	(0.5%)
Transaction by Relative - Yes	**0.2%*** **	**0.1%** **	**0.2%***	**1.7%*** **	-0.1%
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Constant	-0.0%	0.0%	-0.1%	-0.3%	0.1%
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.1%)
Observations	23,069	6,645	4,213	2,210	10,001
R^2	0.007	0.014	0.017	0.039	0.007
Adjusted R^2	0.007	0.013	0.015	0.036	0.006

The table presents the results of the regression for PDMR purchase transactions, grouped by stock exchange list, with abnormal stock returns following the PDMR transaction publication as as the dependent variable. Stock return is calculated as a price change in percent. The data covers PDMR transactions of 828 stocks over 1,608 trading days, compiling 23,069 observations in total split between four stock exchange lists. Standard errors are shown in paranthesis. Bold values indicate statistical significance at α<0.1

*** p-value<0.01, **p-value<0.05, *p-value<0.1

One should comment on the R^2-value of the linear regression given that it is very low across all regressions. That means that our linear regression model only explains a fraction of the total variance in the dependent variable in our data. This is in line with expectations for this type of model, given that it is constructed by only eight variables, most of which are binary, dummy variables, and that it tries to explain a highly complex event that abnormal stock returns represent, especially in uncertain times. Given that almost all the coefficients of the dependent variables showcase statistical significance, with most of them being at the 1% significance level, indicates that the linear regression model has at least a partial explanatory value in the abnormal stock returns.

Finally, we perform a Breusch-Pagan heteroscedasticity test on all regression models, to see if we can determine that the error terms are homoscedastic. Given the high degree of significance in the test across stock exchange lists, we can reject the null hypothesis that the residuals are homoscedastic. This poses a limitation to our regression results, given that one of the implied assumptions of a time-series linear regression is that the variance is constant across the data, without any systematic patterns. Given that the outcome of our heteroscedasticity test showcases that such patterns most likely exist in the

data, the least-squares regression model is not the best-unbiased estimator (Newbold, 2013). This is a limitation in the conclusions that can be drawn from the regression results.

Table 11a. Heteroscedasticity Test - PDMR Purchases

	Stock Exchange List				
	All Cap	Large Cap	Mid Cap	Small Cap	First North
Regression	**83.66*** **	**118.66*** **	**96.74*** **	**94.39*** **	**37.85*** **

The table reports the results of the Breusch-Pagan heteroscedasticity test results for all regression models run on PDMR purchase data. Significant results indicate that we reject the null hypothesis of homoscedasticity. Bold values indicate statistical significance at $\alpha<0.1$.
*** p-value<0.01, **p-value<0.05, *p-value<0.1

Table 10b showcases the results from the regression analysis made on the PDMR sales transactions. In this case, the outcome is not as clear-cut. When looking at the effects of the treatment period on the abnormal stock return following the PDMR trade, we see no significant effect at all on an aggregated level. Once again, these results are in line with those of the t-test outcome, where we also did not see any significant impact of the transaction occurring during the Covid-19 crisis and its subsequent market reaction. Looking across the stock exchange lists, we find statistically significant effects that can be derived from the treatment period for stocks on the Large and Mid Cap list. However, contrary to our hypothesis, this effect seems to be positive for the Mid Cap list, i.e., that is a higher abnormal market return than what can be seen in the control period. This positive sentiment in the treatment period was also seen for some of the stock exchange lists in Welch's t-test, though those results were not statistically significant for any stock exchange list.

In line with the PDMR purchase transactions, almost all the independent variables showed statistical significance in explaining the abnormal market return at the aggregated level. The prevalence of a high-ranking insider selling shares seems to have a substantial negative impact on the following abnormal market return post-publication, with statistical significance at the 1% level. Similarly, having a relative to the PDMR sell shares also has a substantial negative impact at the same statistical significance level. When comparing the effect of these independent variables with the equivalent ones for PDMR purchases, we see that there is an asymmetry in the reaction. That is, when the transaction is a purchase, being a high-ranking PDMR or a relative to the insider increases the positive effect of the trade on the abnormal market return at the aggregated level, while the same factors generate an increased negative affect following a sales transaction. It is also worth noting that the negative effect seems to be larger than that of the positive, suggesting a skew of the amplitude of the effect towards PDMR sales. Transacting in conjunction with the release of a financial report also seems to have a statistically significant negative impact on the abnormal market returns at the 1% level. This negative impact is also symmetrical to the positive effect showcased by the same independent variable for the PDMR purchase trades, though with less of a clear skew towards the negative effect. Once again, it is worth noting that a linear regression method is better, though not perfect, at isolating the effects of individual independent variables. However, it is only able to showcase correlation between the dependent and independent variables and cannot prove any sort of causality.

Table 10b. Regression Results for PDMR Sales Transactions

Dependent Variable: Abnormal Stock Return					
	Stock Exchange List				
	All	Large Cap	Mid Cap	Small Cap	First North
Covid-19 - Yes	-0.0%	**-0.2%*** **	**0.4%*** **	0.3%	-0.1%
	(0.1%)	(0.1%)	(0.1%)	(0.3%)	(0.2%)
Transaction Size of Company (%)	0.0%	0.0%	0.0%	-0.0%	0.0%
	(0.0%)	(0.0%)	(0.0%)	(0.0%)	(0.0%)
High-ranking Insider - Yes	**-0.8%*** **	**-0.3%*** **	**-1.3%*** **	**0.5%***	**-0.7%*** **
	(0.1%)	(0.1%)	(0.1%)	(0.3%)	(0.3%)
Incentive Program Related - Yes	**0.4%***	**-0.2%** **	**0.6%** **	-1.0%	1.1%
	(0.2%)	(0.1%)	(0.3%)	(1.0%)	(0.7%)
Transaction in Reporting Period - Yes	**-0.5%*** **	0.0%	**-0.9%*** **	-0.4%	-0.0%
	(0.1%)	(0.1%)	(0.1%)	(0.3%)	(0.3%)
Market Open on Publication - Yes	**-0.4%*** **	**0.2%***	**-0.2%***	0.1%	**-0.7%*** **
	(0.1%)	(0.1%)	(0.1%)	(0.3%)	(0.2%)
Publication on Reporting Date - Yes	-0.6%	0.6%	**-2.4%*** **	0.4%	-0.7%
	(0.7%)	(0.6%)	(0.7%)	(1.9%)	(1.5%)
Transaction by Relative - Yes	**-0.7%*** **	0.1%	**0.8%*** **	-0.4%	**-1.4%*** **
	(0.1%)	(0.1%)	(0.2%)	(0.3%)	(0.2%)
Constant	**0.2%***	0.1%	-0.1%	**-0.5%** **	0.4%
	(0.1%)	(0.1%)	(0.2%)	(0.2%)	(0.3%)
Observations	8,171	2,204	1,797	714	3,456
R^2	0.014	0.012	0.131	0.014	0.016
Adjusted R^2	0.013	0.009	0.127	0.002	0.014

The table presents the results of the regression for PDMR sales transactions, grouped by stock exchange list, with abnormal stock returns following the PDMR transaction publication as as the dependent variable. Stock return is calculated as a price change in percent. The data covers PDMR transactions of 579 stocks over 1,318 trading days, compiling 8,171 observations in total split between four stock exchange lists. Standard errors are shown in paranthesis. Bold values indicate statistical significance at α<0.1

*** p-value<0.01, **p-value<0.05, *p-value<0.1

When looking at the individual stock exchange level, there seems to be a higher degree of heterogeneity in the statistically significant independent variables for the different stock exchange lists, as compared to the equivalent clear overlap for PDMR purchases. For PDMR sales there is statistical significance among the majority of stock exchange lists for the variables related to high-ranking insiders and the market being open upon publication. However, the correlation of these variables to the abnormal stock returns varies between the stock exchange lists, which weakens the overall conclusion that can be drawn from the results on the aggregated level.

Once again it is worth noting the low R^2-values that are prevalent for the regression analysis. In this case, the R^2-values are higher than that of the results for PDMR purchases, though there are fewer statistically significant variables, with only a minority of the factors showing any significant explanatory value at the aggregated level. Hence, one should be careful in drawing any definitive conclusions from the regression model, other than that directly related to these significant independent variables.

Finally, we perform a Breusch-Pagan test for heteroscedasticity for the PDMR sales transactions as well. Like the PDMR purchases, the null hypothesis

that homoscedasticity is prevalent among the residual terms can be rejected, hence indicating that heteroscedasticity is a problem for these linear regression models as well. However, it worth mentioning is that the level of significance is generally lower for the PDMR sales, but that could also be the result of the smaller sample size among sales transactions.

Table 11b. Heteroscedasticity Test - PDMR Sales

	Stock Exchange List				
	All Cap	Large Cap	Mid Cap	Small Cap	First North
Regression	**48.47*** **	**48.67*** **	**101.16*** **	**14.72***	**36.09*** **

The table reports the results of the Breusch-Pagan heteroscedasticity test results for all regression models run on PDMR sales data. Significant results indicate that we reject the null hypothesis of homoscedasticity. Bold values indicate statistical significance at α<0.1.
*** p-value<0.01, **p-value<0.05, *p-value<0.1

C. Placebo Test

As stated in our Method Section, the purpose of the placebo test was to act as a robustness test to check for any potential overarching time trends that distorts our results. Given this purpose, an ideal outcome would be to have no significant results for the placebo period variable, as this would indicate that the results that we got from the linear regression were not related to a general time trend but rather an exogenous change in the market uncertainty. Given that the placebo period variable was not statistically significantly different from zero when looking across all stock exchange lists, this strengthens the confidence in the results that we got from our linear regression, as this would suggest that the statistically significant results, we got from those tests were not related to a general time trend. When looking at the individual stock exchange lists, we find some statistically significant results for Large, Mid, and Small Cap. However, for the two former lists, this result contrasts with the linear regression results, as this result is negative instead of positive, hence still suggesting that there is no general increase in abnormal market returns over time for these lists – rather the opposite. For Small Cap, there seems to be quite a large positive time trend for abnormal market returns following PDMR purchase transactions. However, given that we did not derive any conclusions due to statistical insignificance in our regression results for this stock exchange list, this does not impact our ability to draw conclusions. One should also be careful to draw major conclusions from the result from Small Cap given that the small sample size for this list makes its results more prone to result from distortions due to noise in the data.

Table 12a. Placebo Test - Regression Results for PDMR Purchase Transactions

Dependent Variable: Abnormal Stock Return					
	Stock Exchange List				
	All	Large Cap	Mid Cap	Small Cap	First North
Placebo Period - Yes	-0.1%	**-0.1%** **	**-0.3%** **	**0.7%*** **	-0.3%
	(0.1%)	(0.1%)	(0.1%)	(0.2%)	(0.2%)
Observations	12,089	3,943	2,339	1,231	4,576

The table presents the results of the regression for PDMR purchase transactions, grouped by stock exchange list, with abnormal stock returns following the PDMR transaction publication as as the dependent variable. Stock return is calculated as a price change in percent. Only the placebo period variable is included in the table, but the same independent variables as were used in the normal regression model were used when running the regression. Standard errors are shown in paranthesis. Bold values indicate statistical significance at α<0.1
*** p-value<0.01, **p-value<0.05, *p-value<0.1

Table 12b. Placebo Test - Regression Results for PDMR Sales Transactions

Dependent Variable: Abnormal Stock Return					
	Stock Exchange List				
	All	Large Cap	Mid Cap	Small Cap	First North
Placebo Period - Yes	**-0.6%*** **	**-0.3%** **	**-0.6%*** **	0.1%	-0.2%
	(0.2%)	(0.1%)	(0.2%)	(0.3%)	(0.4%)
Observations	4,139	1,080	1,065	441	1,553

The table presents the results of the regression for PDMR purchase transactions, grouped by stock exchange list, with abnormal stock returns following the PDMR transaction publication as as the dependent variable. Stock return is calculated as a price change in percent. Only the placebo period variable is included in the table, but the same independent variables as were used in the normal regression model were used when running the regression. Standard errors are shown in paranthesis. Bold values indicate statistical significance at $\alpha<0.1$
*** p-value<0.01, **p-value<0.05, *p-value<0.1

For PDMR sales transactions the placebo period variable is statistically significant when looking across all stock exchange lists. This would suggest that there might be an overarching time trend of an increased negative abnormal stock return following the publication of a PDMR sales transaction. However, one should remember that the purpose of the placebo test is to examine whether there is a general time trend that distorts the results in the covid treatment period. For this outcome to be distortive we would have to see the same negative factor in the results for the covid treatment variable, as that would suggest that the outcome would rather be the outcome of an overarching time trend rather than the exogenous change in uncertainty in the distinct period. Since our results from the linear regression model indicate that there is no significant change in the abnormal market return for PDMR sales transactions during the covid treatment period as compared to the control period, the outcome of the placebo test does not impact the interpretation of our initial results. However, it does suggest that one should be more careful when drawing definitive conclusions for PDMR sales transactions, as there seem to be underlying time trends in the data that do not exist for PDMR purchase transactions. Though it is worth bearing in mind that the PDMR sales transaction data is more prone to noise given its smaller sample size, which increases the risk of distorted results in the placebo test. Regardless, this suggested time trend from the placebo test for PDMR sales transactions should be considered a limitation in our research that negatively impacts the conclusions that we can make.

Discussion

A. Results of Hypotheses

As previously present, we have found significant results that the market reactions to PDMR purchase transactions were more distinct during the treatment period than during the control period, while no significant difference was prevalent for sales transactions. In this section of our paper, we will discuss the results and attempt to explain our outcomes in light of current literature. First, we will revisit our in-going hypotheses:

Hypothesis 1: *There will be an increased market reaction to PDMR transactions for the Covid-19 period.*

In general, we found increased market reactions to PDMR transactions for the Covid-19 period. Table 8 shows a positive 0.39% change in returns on purchases across all stock exchange lists (significant the p-value<0.01 level). We

did not see the same effect on sales.

The result is in line with how Loh and Stulz (2018) found that market reactions to analyst revisions differed between good and bad times. However, Loh and Stulz (2018) found increased market reactions to both upwards revisions and downwards revisions. We, therefore, expected the reaction to be increased both for purchases and sales. One possible reason that could explain our outcome is that the signaling value of purchases is higher than that of sales ("only one reason to sell") (Lynch, 2000s). That is a fact that makes it problematic to compare analyst revisions with PDMR transactions (signaling asymmetry). An additional explanation to this lack of symmetry in results between transaction types could be that of the anchoring effect (Kahneman, 2011) . If investors have adjusted their reference point downwards in uncertain times, they might see a PDMR purchase as deviating additionally from their expectations than what they would have in normal market conditions. This could explain why we see additional market reactions for PDMR purchase transactions but not for sales. We note that our outcome is in line with what Lakonishok and Lee (2001) found during their study; they were also unable to show significant increased abnormal stock returns to PDMR sales transactions. Like this paper, they did achieve it for purchases. Previous research, mainly Lakonishok and Lee (2001) showed that increased reactions to PDMR transactions are caused by the informational value derived by the market from said transaction. Interpreting our results, we find that the informational gap between investors and PDMRs likely was higher during the treatment period than the control period. It is a plausible conclusion that would be in line with previous research.

Our result indicates an increase in abnormal stock returns following PDMR purchase transaction announcements in uncertain times, while the same cannot be said for sales, hence partly confirming our hypothesis. This would suggest that investors attribute additional value to PDMR purchases in uncertain times, but do not attribute equal informational value to PDMR sales.

Hypothesis 2: *The intensity of the increased market reactions will vary across sectors. We expect to see greater market reactions among stocks in the industries: 'Automobiles and Parts', 'Energy' and 'Travel and Leisure'.*

We found the intensity of the increased market reactions to be varying across sectors. For purchases, the largest significant effects were seen for 'Banks' (Table 9a). For sales, the largest significant effect was seen for 'Telecommunications'. At a first glance, the indication is that the significant effects are larger for industries (e.g., banks and telecommunications) where the financing risk is high. Following the outbreak of the pandemic, the credit markets were largely uncertain and little information reached investors for the first part (Kammarkollegiet, 2020). One plausible explanation for the increased market reactions to financing heavy businesses could be that information was scarce, and hence the relative additional value carried by PDMR transactions was elevated. While there are many plausible explanations, another one worth mentioning is that companies in both the 'Banks' and 'Telecommunications' sectors tend to bear a lot of debt, and the crisis made financing more challenging (Kammerkollegiet, 2020). A part of the informational value of the PDMR transactions could have been that these businesses were not planning large

future write-offs which could explain part of the increased market reactions. Should concerns regarding financing outlook be an area where information was scarce, then we would expect increased reactions. This is also in line with the findings by Kacperczyk et al (2017).

In line with our hypothesis, 'Automobiles and Parts' was one of the industries that saw the highest increase in abnormal stock returns during the pandemic, at least for PDMR purchases. This is in line with our hypothesis and would suggest that sector exposure to default probability has at least some explanatory value in market reaction increases in times of uncertainty (Standard & Poor's, 2022). However, given that we did not see the same effect for companies in the 'Energy' and 'Travel and Leisure' sectors, said connection is likely not very prominent. For 'Travel and Leisure' the outcome was even directly contradictory to what we had expected, with a decrease in market reactions to PDMR purchase transaction during the pandemic as compared to normal market conditions. Despite not adhering to our expectations, this outcome could be explained by the study by Hirshleifer, Lim and Teoh (2009). 'Travel and Leisure' was one of the most, if not the most, impacted sectors of the pandemic, with international travels reduced by more than 90% following the outbreak (Borko, 2020). Given the increased media and analyst attention that such an event has on companies in the sector, there might have been an increase in the intensity of news flow and a subsequent reduction in the informational gap between investors and insiders. Hence, in line with the results of Hirshleifer, Lim and Teoh (2009) the individual informational value of an additional news event, such as the publication of a PDMR transaction, might have been reduced to such an extent that it is considered to have less value than during normal market conditions. This would explain this outcome, despite not being in line with our expectations.

The same reasoning would apply to the 'Health Care' sector that also saw no significant increases in market reactions in the treatment period. The pandemic may simply have drawn so much attention to the sector that the information value of the PDMR transactions became redundant. An example of this could be the Nasdaq Large Cap company Getinge. They are a manufacturer of medicinal technology equipment. A substantial product line of theirs is that of respiratory equipment. During the height of the pandemic, they released an elevated number of press releases, and communication to the market about new production targets and the means to get there (Teknikföretagen, 2020). Hence, the results are not as unexpected as one could think at first.

To conclude, our results indicate heterogeneity among the intensity of market reactions following PDMR transactions between different sectors. There are some indications that the default risk of companies within the sector impacts how the abnormal stock returns develop in uncertain times. However, contrary to our hypothesis, there instead seems to be a negative correlation between the media and analyst exposure of a sector and the increase in market reactions during uncertain times given the possible reduction of the informational gap between investors and insiders.

Hypothesis 3: *Reactions for stocks listed on markets with looser regulation requirements will be larger. This implies that we expect reactions on Nasdaq First North to be greater than on the Main List of Nasdaq Stockholm.*

We found a larger increase in market reactions on Nasdaq First North than on the Main List of Nasdaq Stockholm. The results were in line with expectations and confirms our hypothesis. We noted the largest reaction on First North, which adhere to looser regulatory requirements (Nasdaq, 2019), and the smallest reaction on Large Cap. We note that our findings are in line with the previous by Alldredge and Cicero (2015).

As equity markets operate under semi-strong efficiency (i.e., they include all public information in the pricing), we expected this result. There is greater visibility on Main List equities and the market has more information and the additional incremental informational value of PDMR transactions is hence lower than for First North. It is reasonable to conclude that this effect can derive from the efficient market hypothesis (Fama, 1970).

Another plausible explanation to our result is the relatively higher market liquidity on the Main List as opposed to First North. Low volumes generally result in higher volatility, which for this study would imply larger market reactions to PDMR transactions announcements. In April 2022, the average number of daily transactions per company on the Nasdaq Stockholm Main List was ~2,300 trades whereas the same number for First North was ~340 trades (Nasdaq, 2022b).

Table 13. Results of Hypotheses

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**
Result	Mostly Confirmed	Mostly Rejected	Confirmed

The table above summarizes the outcome of the hypotheses that were introduced in the beginning of this paper. The hypothesis can either be Confirmed (validated in its entirety), Mostly Confirmed (most parts of it validated while others were rejected) or Mostly Rejected (most parts of it rejected while others were validated).

B. Surprises

One of the most surprising outcomes of our study is that we generally found a lack of symmetry between reactions to PDMR purchases and PDMR sales. We expected industries that saw large positive reactions to purchases to also see large negative reactions to sales and vice versa. While this holds for some industries, e.g., industrials, we did not see it for the majority of the sectors. For the food and beverages sector, we even saw significant increases of abnormal stock returns upon PDMR transaction announcements, regardless of whether it concerned a purchase or sale. The study by Lakonishok and Lee (2001) also found similar results. Their explanation was that insiders tend to trade against momentum and that the informational value of purchases was higher than for sales. That means when PDMRs purchase on bad days, the market will react positively, and, when PDMRs sell on good days, the informational value of said sale will not alone contract the positive effect of the momentum.

C. Limitations

As described in previous sections, our research methodology has been designed to reduce and test for limitations in our results. Despite this, it is not

possible to completely mitigate external disturbing factors that have a distorting effect on our findings.

To begin with, given that we are measuring the abnormal stock returns based on opening and closing day prices, there is a lot of other events and information that is also priced throughout the trading day that is hard to control for. Choosing to define abnormal stock returns as the return throughout the entire trading day is in line with our main reference and is the overall superior approach as discussed in the Data Section. However, it does make it more difficult to isolate the return directly linked to the publication of the PDMR transaction. For example, in the case that the company makes a press release with positive sentiment on that same day, the market can be expected to have a positive reaction to said news that is unrelated to the publication of the PDMR transaction, hence having distorting effects on our results. We have tried to limit this effect as much as possible by adjusting our approach to how abnormal stock returns are measured depending on publication time and by incorporating the publication of financial results as a control factor in our regressions. This creates the tightest possible interval that can be achieved with opening and closing prices, and controls for one of the most information intense events that a company can have, though the results will still suffer due to price effects from unrelated informational events.

As discussed in the results of the placebo test, there does not seem to be any overarching time trends related to the development of abnormal stock returns following PDMR transactions, i.e., that there is a trend that the market reaction increases or decreases following the publication that is unrelated to the level of uncertainty in the markets. This increases the confidence in our research methodology as that means that we to a larger extent can isolate the effect of the change in market uncertainty. However, the prevalence of a seemingly negative time trend for PDMR sales transactions, i.e., that the market reacts acts in a more negative fashion as time progresses, limits the accuracy of the conclusions that can be drawn for the sales transactions. That is because the inconclusive result for PDMR sales transactions in our study might be due to two opposing effects, namely the negative time trend and a potentially positive effect from market uncertainty, which neutralizes the total effect. We can only speculate regarding whether that is the case or not, but such a possibility limits the extent of conclusions one can draw for PDMR sales transactions.

As discussed in the Data and Method Sections, in addition to our treatment variable our regression model includes seven control variables to isolate the effect of a change in market uncertainty. Furthermore, we have also tested for correlation and multicollinearity for additional fixed-effects variables and found no relevant, significant results. Despite this effort, one should not neglect the possibility that the model suffers from omitted variable bias, whereby a factor that correlates with the treatment variable but is not included in the regression model, distorts the results. Examples of potential omitted variables include PDMR trading behavior, where the Covid-19 pandemic might have changed the frequency and size of their transactions in relation to their personal wealth, that the market reacts to. Furthermore, there might have been increased media attention related to the PDMR transactions during the pandemic that might drive the market reaction, rather than it being the change of market uncertainty.

We found it difficult to gather accurate data and develop a methodology for how to control for trading behavior and media attention, which is the reason they were not included in the first place. Though we do not have any evidence that suggests that these would have an impact on the results, the reader should be aware of our inability to control for them which creates a risk for omitted variable bias.

As was mentioned in the results, the R^2-values of our regression model were low. This implies that our regression model is not exhaustive and only captures a few of the explaining factors that derive the dependent variable. However, given the complexity of the variable that we are trying to explain, i.e., abnormal stock returns, it is expected that our linear model will not be complete. Regardless, most of the variables that we do include in the model are statistically significant, suggesting that they provide value to the model, despite the limited effect size. The prevalence of heteroscedasticity in our data set was presented in the Results Section. This implies that a linear regression model is not the optimal way that one should study this phenomenon. However, it does not mean that the results of the regression model are invalid, but that there are better ways to model it. The reader should be aware of this and the fact that it impacts the ability to draw conclusions based on our findings.

Finally, one should be aware of the inherent limitation for some sectors in how we calculate our abnormal stock returns. As presented in the Data Section, this is done by subtracting the appropriate sector index returns from the share performance of the individual stock. Generally, this results in a measure of the isolated performance of the individual stock, where macro- and sector developments have been filtered out. However, for niche sectors, their value-weighted sector index is to a large extent driven by a few large companies. This means that such a sector index would disproportionally be impacted by the individual stock performance of those large companies. This would in turn decrease the calculated abnormal stock return compared with an optimal setting since the performance of the individual share disproportionally impacts the performance of the sector index that is subsequently subtracted to derive the abnormal stock return. For example, the sector index for the media industry (SX4030PI) consists of only four unique companies, whereby the abnormal stock returns for stocks in this sector can be expected to be lower than what they would have been in an ideal setting (Nasdaq, 2020). However, this only has an impact on the amplitude of the effect, but not the direction of it, and is also limited to a few niche sectors rather than being a problem with the entire data set. Regardless, the reader should be aware of this limitation in our results.

Final Remarks

A. General

The extraordinary uncertainty event that was the Covid-19 pandemic had an evident impact on financial markets. In this climate, uncertainty reached high levels, stock market volatility was elevated and PDMRs executed an increasing number of transactions (SFSA, 2022). PDMR transactions have, in prior research, been proved to bring informational value about the upcoming performance of companies. Considering this, we set out to study market reactions to PDMR transaction announcements before and during the pandemic and

compare market reactions to insider transactions during these periods. There have been no prior studies investigating PDMR transaction announcement reactions during times of uncertainty; in addition, most adjacent studies have been conducted in the United States (Table 1). In the light of this, we find this study to be an important contributor to a better understanding of how authorities should design PDMR regulations and how corporations can position themselves around these announcements.

Our study investigates whether there were increased market reactions during times of uncertainty, proxied by the Covid-19 pandemic.

On the aggregated level in our t-tests, we find that PDMR purchase announcements during the treatment period gave 0.39% daily excess returns at p-level<0.01. Looking at individual lists, we saw significant results for all lists but Small Cap. For our significant results, we found positive increased market reactions for all lists. The effect was larger on smaller lists than on larger lists. This is in line with our expectation that insider has a larger informational advantage at smaller companies and hence each transaction carries a higher relative informational value. We did not find aggregated significant results for PDMR sales announcements. However, we did find significant results for individual lists.

In our sector analysis, we found increased market reactions to differ by industry. In general, we found larger reactions, both positive and negative, for industries that carry a lot of financial risks. Interestingly, we did not find large positive reactions in the 'Travel and Leisure' and 'Health Care' sectors – indicating that all the media and analyst attention on the industries during the pandemic has diminished the informational value of each PDMR transaction.

The regression analysis for purchases shows that the market environment can explain 0.3% (significant at p<0.01) of the daily excess returns following the publication of a PDMR purchase transaction during the Covid-19 pandemic, while no significant results were found for PDMR sales transactions. Note that this is largely in line with the results from the t-test.

Given the evident increase of the PDMR informational advantage during the crisis (with many industries having more than a 1% increase in abnormal stock returns during the Covid-19 pandemic), we think that there are good grounds for the regulator to investigate what actions can be taken to level the playing field. We find additional regulatory restrictions to be an appealing measure for this case. While none of the alternatives is perfect, measures could include pre-emptily reporting trades and restricting trades during extraordinary uncertainty peaks; especially when the company has not yet informed the market of how an uncertainty event is having an impact on them.

The results of our study are largely in line with our key references; Lakonishok and Lee (2001) and Loh and Stulz (2018). Like the first, we find a larger effect for purchases than for sales and larger effects for smaller companies (lists) than for larger ones. Similarly, to the latter, we found increased market reactions during uncertain times. Our study can hence be used to validate the findings of said studies. However, while our results validate their key points; there are some incongruities. We saw no aggregate significant effect for sales, yet Loh and Stulz (2018) did find large significant reactions for downwards reactions. This highlights that the papers are not fully comparable as analyst

revisions always carry informational value whereas PDMR transactions seem to mostly carry informational value for purchases.

B. Future Research

Since the outbreak of the pandemic, much research work has been drawn to this uncertain event. Researchers have been attracted to unprecedented conditions of the crisis and how it has both impacted corporations on the individual level and the wider capital markets. This report is a much-needed contribution to better understand PDMR transaction effects. For future research on this topic, we have a few suggestions on areas where we see value in additional studies. As mentioned in the Data Section, the ideal study would be to design a research method with a synthetically exogenous change in uncertainty. While this is not possible in practice, further research could include larger data sets which would generate more significant results and hence serve as validation for this study.

In this paper, the treatment period is defined as the period with high degrees of Covid-19 restrictions. There are other alternatives on how to define the treatment period. One possible way would be to use market volatility as a proxy for uncertainty (e.g., CBOE VIX, or similar). By using an index that is updated with higher frequency, the uncertainty effect could plausibly be easier to isolate.

In addition, future research could further break down a period of uncertainty. By reviewing different parts of the uncertainty cycle, we expect that interesting results could be found. One way to do it would be to define each uncertainty day with a category. Categories could be based on which topics are dominating media for that day. Example categories could be i.e., Economic Slowdown, Inflation, Deflation and Unemployment.

Finally, additional research could be constructed as a playbook for corporations that are on how to build and retain the confidence of the market. By studying more distinct components that can explain how markets react to transactions depending on characteristics, studies can aid executives in designing PDMR policies, but also help in optimizing share buyback programs. Our results evidently point out that there are right and wrong strategies available. Hence, responsible regulators, owners and executives with fiduciary duties should be obliged to be aware and take into consideration the findings of this study.

References

Alldredge, Dallin M., and David C. Cicero. (2015). *Attentive insider trading.* Journal of Financial Economics 115.1 (2015): 84-101.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. (2016). *Measuring economic policy uncertainty*. The quarterly journal of economics 131.4 (2016): 1,593-1,636.

Belgacem, Aymen, Anna Creti, Khaled Guesmi, and Amine Lahiani. (2015). *Volatility spillovers and macroeconomic announcements: evidence from crude oil markets.* Applied Economics 47.28 (2015): 2,974-2,984.

Biggerstaff, Lee, David Cicero, and M. Babajide Wintoki. (2020). *Insider trading patterns*. Journal of Corporate Finance 64 (2020): 101654.

Borko, Seth, Wouter Geerts and Haixia Wang. (2020, September). *The Travel Industry Turned Upside Down.* McKinsey.com. Retrieved from: https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/the-travel-industry-turned-upside-down-insights-analysis-and-actions-for-travel-executives. Accessed 14 May 2022.

Busse, Jeffrey A., and T. Clifton Green. (2002). *Market efficiency in real time*. Journal of Financial Economics 65.3 (2002): 415-437.

Chiu, Junmao, Huimin Chung, Keng-Yu Ho and Chih-Chiang Wu. (2018). *Investor sentiment and evaporating liquidity during the financial crisis*. International Review of Economics & Finance 55 (2018): 21-36.

Christie, William G., and Roger D. Huang. (1995). *Following the pied piper: Do individual returns herd around the market?*. Financial Analysts Journal 51.4 (1995): 31-37.

Deloitte. (2020). *COVID-19 will permanently change e-commerce in Denmark*. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/dk/Documents/strategy/e-commerce-covid-19-onepage.pdf. Accessed 10 Apr 2022.

Eckbo, B. Espen, and David C. Smith. (1998). *The conditional performance of insider trades*. The Journal of Finance 53.2 (1998): 467-498.

Eggers, Andrew C., Guadalupe Tuñón, and Allan Dafoe. (2021). *Placebo Tests for Causal Inference*. Unpublished working paper.

Fama, Eugene F. (1970). *Efficient capital markets: A review of theory and empirical work*. The journal of Finance 25.2 (1970): 383-417.

Hirshleifer, David, and Tyler Shumway. (2003). *Good day sunshine: Stock returns and the weather.* The journal of Finance 58.3 (2003): 1,009-1,032.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh. (2009). *Driven to distraction: Extraneous events and underreaction to earnings news*. The Journal of Finance 64.5 (2009): 2,289-2,325.

IMF. (2020, October 31). *World Economic Outlook October 2020*. IMF. Retrieved from: https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020#Full%20Report%20and%20Executive%20Summary. Accessed 10 Apr 2022.

Kacperczyk, Marcin, Jaromir Nosal, and Savitar Sundaresan. (2017). *Market power and informational efficiency*. Unpublished working paper.

Kahneman, Daniel. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Kammarkollegiet. (2020). *Kapitalförvaltningens kvartalsrapport Q1 2020.* Kammarkollegiet.se. Retrieved from: https://www.kammarkollegiet.se/download/18.1bbf82e91715d868181363e3/1587386849084/Kvartalsrapport_2020-Q1%201.0b.pdf. Accessed 7 May 2022.

Lakonishok, Josef, and Inmoo Lee. (2001). *Are insider trades informative?*. The Review of Financial Studies 14.1 (2001): 79-111.

Loh, Roger K., and René M. Stulz. (2018). *Is sell-side research more valuable in bad times?.* "The journal of finance 73.3 (2018): 959-1013.

Loewenstein, George. (1996). *Out of control: Visceral influences on behavior*. Organizational behavior and human decision processes 65.3 (1996): 272-292.

Lynch, Peter, and John Rothchild. (2000). *One up on Wall Street: how to use what you already know to make money in the market*. Simon and Schuster.

McKinsey. (2020, November 2). *When nothing is normal: Managing in extreme uncertainty*. McKinsey. Retrieved from: https://www.mckinsey.com/business-functions/risk-and-resilience/our-insights/when-nothing-is-normal-managing-in-extreme-uncertainty#. Accessed 10 Apr 2022.

Mehndiratta, Neetu, and Shuchi Gupta. (2010). *Impact of dividend announcement on stock prices*. International Journal of Information Technology and Knowledge Management 2.2 (2010): 405-410.

Nasdaq. (2019, 1 January). *Regelverk för emittenter – Nasdaq Stockholm*. Retrieved from: https://www.nasdaq.com/docs/Nasdaq%20Stockholms%20regelverk%20f%C3%B6r%20emittenter%20-%201%20januari%202019.pdf. Accessed 7 May 2022.

Nasdaq. (2020). *SX4030PI, OMX Stockholm Media Pi*. Nasdaq.com. Retrieved from: http://www.nasdaqomxnordic.com/indexes/index_info?languageId=3&Instrument=SE0004383669. Accessed 7 May 2022.

Nasdaq. (2021a). *Nasdaq European Markets*. Nasdaq.com. Retrieved from: https://www.nasdaq.com/docs/2021/10/06/Nasdaq_First_North_%20GM_%20Introduction_2020_1.pdf. Accessed 7 May 2022.

Nasdaq. (2021b, October). *From Nasdaq First North Growth Market to the Nasdaq Stockholm Main Market*. Nasdaq.com. Retrieved from: https://www.nasdaq.com/docs/2021/10/14/Listing_Transfer_Guide_to_Nasdaq_Stockholm_2021.pdf. Accessed 7 May 2022.

Nasdaq. (2022a). *Global Index Watch (GIW) Directory*. Indexes.Nasdaqomx.Com. Retrieved from: https://indexes.nasdaqomx.com/Index/Directory. Accessed 10 Apr 2022.

Nasdaq. (2022b). *Statistics from Nasdaq Nordic Exchange April 2022*. Nasdaq.com. Retrieved from: https://view.news.eu.nasdaq.com/view?id=b5fb0dc27fadac3b2354b12dd50d5cbd6&lang=en. Accessed 15 May 2022.

Newbold, Paul, William Carlson and Betty Thorne. (2013). *Statistics for Business and Economics: Eight Edition*. United States: Pearson Education, Inc.

Official Journal of the European Union. (2014, 12 June). *Market Abuse Regulation*. Eur-lex.Europa.Eu. Retrieved from: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014R0596&from=EN. Accessed 2 May 2022.

Oxford University. (2022). *Covid-19 Government Response Tracker*. Bsg.ox.ac.uk. Retrieved from: https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker. Accessed 1 May 2022.

Schmalz, Martin C., and Sergey Zhuk. (2019). *Revealing downturns*. The Review of Financial Studies 32.1 (2019): 338-373.

Seyhun, H. Nejat. (1986). *Insiders' profits, costs of trading, and market efficiency*. Journal of financial Economics 16.2 (1986): 189-212.

Standard & Poor's. (2022, January). *Industries Most And Least Impacted By COVID-19 From A Probability Of Default Perspective - January 2022 Update*. Spglobal.Com. Retrieved from: https://www.spglobal.com/marketintelligence/en/news-insights/blog/industries-most-and-least-impacted-by-covid-19-from-a-probability-of-default-perspective-january-2022-update. Accessed 10 Apr 2022.

Suneson, Grant. (2020). *Industries Hit Hardest By Coronavirus In The US Include Retail, Transportation, And Travel*. WLST. Retrieved from: https://eu.usatoday.com/story/money/2020/03/20/us-industries-being-

devastated-by-the-coronavirus-travel-hotels-food/111431804/. Accessed 10 Apr 2022.

Swedish Financial Supervisory Authority (SFSA). (2022). *PDMR transactions*. Swedish Financial Supervisory Authority. Retrieved from: https://www.fi.se/en/markets/investors/pdmr-transactions/. Accessed 10 Apr 2022.

Teknikföretagen. (2020, 7 April). *Så kan Geting möta vårdens behov*. Tekniforetagen.se. Retrived from: https://t.teknikforetagen.se/samhallsutveckling/genom-samarbete-moter-getinge-vardens-behov/. Accessed 7 May 2022.

The Guardian. (2020, March 18). *Italy Records Its Deadliest Day Of Coronavirus Outbreak With 475 Deaths*. The Guardian. Retrieved from: https://www.theguardian.com/world/2020/mar/18/coronavirus-lockdown-eu-belgium-germany-adopt-measures. Accessed 10 Apr 2022.

Appendix A: Random Sample from Data Set

Appendix A. Random Sample of Dataset

Publ. Date	Ticker	Sector Index	Stock Exchange List	Covid	Trans.Size	Insider.Role	Incentive.Progr.	Report.Period	Market.Open	Report.Day	Relative	Abnormal Stock Return
2017-09-13	OM: PEAB B	SX5010PI	Large Cap	N	119 ppm	N	N	N	Y	N	N	0.35%
2017-11-25	OM: BRAV	SX5010PI	Large Cap	N	1,861 ppm	Y	N	Y	N	N	N	-1.30%
2018-03-20	OM: SEYE	SX5020PI	First North	N	404 ppm	Y	N	Y	Y	N	N	-2.72%
2018-05-17	OM: AZA	SX3010PI	Large Cap	N	133 ppm	Y	N	N	N	N	N	-0.43%
2018-10-23	OM: TANGI	SX4020PI	First North	N	4,531 ppm	Y	N	N	N	N	Y	-2.91%
2018-10-26	OM: SKF B	SX5510PI	Large Cap	N	8 ppm	N	N	Y	N	N	Y	-1.91%
2018-11-13	OM: TOBII	SX101010PI	Mid Cap	N	897 ppm	N	Y	N	Y	N	N	-3.60%
2018-11-18	OM: FRISQ	SX101010PI	First North	N	495 ppm	N	N	Y	N	N	N	2.25%
2019-05-02	OM: MAGI	SX4020PI	First North	N	57 ppm	N	N	N	Y	N	N	-1.39%
2019-05-14	OM: SKA B	SX5010PI	Large Cap	N	0 ppm	N	N	N	N	N	N	0.20%
2019-11-06	OM: SHB B	SX3010PI	Large Cap	N	260 ppm	Y	N	N	Y	N	N	-1.09%
2020-01-09	OM: SKIS B	SX4050PI	Mid Cap	N	3,190 ppm	N	N	N	Y	N	N	-0.68%
2020-08-27	OM: BEGR	SX5510PI	Small Cap	Y	17,456 ppm	N	N	N	Y	N	Y	4.14%
2020-11-27	OM: RENEW	SX5510PI	First North	Y	2,045 ppm	N	N	Y	Y	Y	N	-1.17%
2021-02-08	OM: MANG	SX3020PI	First North	Y	414 ppm	Y	N	N	Y	N	N	0.93%
2021-02-18	OM: QLIRO	SX3020PI	Small Cap	Y	556 ppm	N	N	N	Y	N	N	-7.89%
2021-03-11	OM: SOBI	SX20PI	Large Cap	Y	24 ppm	N	N	N	Y	N	N	-0.73%
2021-04-13	OM: LUG	SX5510PI	Large Cap	Y	556 ppm	N	N	N	N	N	N	1.94%
2021-05-06	OM: TEL2 B	SX15PI	Large Cap	Y	138 ppm	N	N	N	N	N	N	-1.47%
2021-05-20	OM: FAG	SX5010PI	Mid Cap	Y	174 ppm	N	N	N	Y	N	N	-3.97%

The above table shows a random sample of 20 PDMR transactions from the dataset. The data is not meant to be considered representative for the entire dataset, but rather to help the reader understand how the data has

Appendix B: Sector Index Summary

Appendix B. Sector Index per Industry

Sector	ICB-code	Sector Index	Index ISIN
Automobiles and Parts	4010	SX4010PI	SE0004383495
Banks	3010	SX3010PI	SE0004383792
Basic Resources	5510	SX5510PI	SE0004383347
Chemicals	5520	SX5520PI	SE0004383313
Construction and Materials	5010	SX5010PI	SE0004383396
Consumer Products and Services	4020	SX4020PI	SE0004383545
Energy	6010	SX60PI	SE0004383263
Financial Services	3020	SX3020PI	SE0004383875
Food, Beverage and Tobacco	4510	SX4510PI	SE0004383511
Health Care	2010	SX20PI	SE0004383594
Household & Personal Products	3030	SX30PI	SE0004383784
Industrial Goods and Services	5020	SX5020PI	SE0004383412
Media	4030	SX4030PI	SE0004383669
Personal Care, Drug and Grocery Stores	4520	SX4520PI	SE0000744070
Real Estate	3510	SX35PI	SE0004383842
Retail	4040	SX4040PI	SE0004383636
Technology	1010	SX101010PI	SE0004383917
Telecommunications	1510	SX15PI	SE0004383701
Travel and Leisure	4050	SX4050PI	SE0004383685
Utilities	6510	SX65PI	SE0004383743

The table reports the sector index used to calcualte abnormal stock returns for stocks in each industry, with their respective ISIN-number. For some sectors no sub-sector index is available, in that case the broader main sector index has been used instead.

Appendix C: Descriptive Statistics Split by Treatment Period

Appendix C1. Descriptive Statistics Independent Variables - Pre-Covid (Control Period)

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Transaction Type	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
Purchases	12,089	*74%*	3,943	*78%*	2,339	*69%*	1,231	*74%*	4,576	*75%*
Sales	4,139	*26%*	1,080	*22%*	1,065	*31%*	441	*26%*	1,553	*25%*
Sector	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
Automobiles and Parts	67	*0%*	-	-	57	*2%*	-	-	10	*0%*
Banks	328	*2%*	279	*6%*	49	*1%*	-	-	-	-
Basic Resources	528	*3%*	327	*7%*	26	*1%*	79	*5%*	96	*2%*
Chemicals	222	*1%*	-	-	-	-	-	-	222	*4%*
Construction and Materials	1,740	*11%*	959	*19%*	172	*5%*	191	*11%*	418	*7%*
Consumer Products and Services	944	*6%*	115	*2%*	257	*8%*	185	*11%*	387	*6%*
Energy	324	*2%*	40	*1%*	4	*0%*	22	*1%*	258	*4%*
Financial Services	471	*3%*	94	*2%*	222	*7%*	2	*0%*	153	*2%*
Food, Beverage and Tobacco	198	*1%*	8	*0%*	123	*4%*	-	-	67	*1%*
Health Care	3,057	*19%*	282	*6%*	1,047	*31%*	289	*17%*	1,439	*23%*
Industrial Goods and Services	3,169	*20%*	1,403	*28%*	642	*19%*	282	*17%*	842	*14%*
Media	128	*1%*	-	-	55	*2%*	1	*0%*	72	*1%*
Personal Care, Drug and Grocery Stores	155	*1%*	24	*0%*	23	*1%*	-	-	108	*2%*
Real Estate	817	*5%*	493	*10%*	252	*7%*	-	-	72	*1%*
Retail	585	*4%*	303	*6%*	138	*4%*	-	-	144	*2%*
Technology	2,178	*13%*	71	*1%*	184	*5%*	447	*27%*	1,476	*24%*
Telecommunications	920	*6%*	598	*12%*	13	*0%*	41	*2%*	268	*4%*
Travel and Leisure	357	*2%*	27	*1%*	140	*4%*	117	*7%*	73	*1%*
Utilities	40	*0%*	-	-	-	-	16	*1%*	24	*0%*
Insider Role	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
Non-material	11,709	*72%*	4,232	*84%*	2,232	*66%*	1,090	*65%*	4,155	*68%*
Material	4,519	*28%*	791	*16%*	1,172	*34%*	582	*35%*	1,974	*32%*
Report Period	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
No	12,423	*77%*	3,964	*79%*	2,260	*66%*	1,260	*75%*	4,939	*81%*
Yes	3,805	*23%*	1,059	*21%*	1,144	*34%*	412	*25%*	1,190	*19%*
Market Open	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
Closed	4,783	*29%*	1,285	*26%*	896	*26%*	598	*36%*	2,004	*33%*
Open	11,445	*71%*	3,738	*74%*	2,508	*74%*	1,074	*64%*	4,125	*67%*
Report Day	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
No	16,016	*99%*	4,958	*99%*	3,342	*98%*	1,637	*98%*	6,079	*99%*
Yes	212	*1%*	65	*1%*	62	*2%*	35	*2%*	50	*1%*
Relative	**16,228**	***100%***	**5,023**	***100%***	**3,404**	***100%***	**1,672**	***100%***	**6,129**	***100%***
No	11,990	*74%*	4,061	*81%*	2,721	*80%*	1,232	*74%*	3,976	*65%*
Yes	4,238	*26%*	962	*19%*	683	*20%*	440	*26%*	2,153	*35%*

The table above represents descriptive statistics across Stock Exchange Lists for the independent dummy variables covering all transaction in the control period (Pre-Covid), covering in total 16,228 transactions. "-" indicates that there is no transaction for that particular combination of variables.

Appendix C2. Descriptive Statistics Independent Variable: Trans.Size - Pre-Covid (Control Period)

Stock Exchange List	N	Mean	Median	Std. Dev.	Min	Max
All	**16,228**	**6 ppm**	**0.14 ppm**	**43 ppm**	**~ 0 ppm**	**7,205 ppm**
Large Cap	5,023	6 ppm	0.01 ppm	39 ppm	~ 0 ppm	1,031 ppm
Mid Cap	3,404	3 ppm	0.09 ppm	26 ppm	~ 0 ppm	1,118 ppm
Small Cap	1,672	5 ppm	0.20 ppm	33 ppm	~ 0 ppm	797 ppm
First North	6,129	9 ppm	0.36 ppm	57 ppm	~ 0 ppm	7,205 ppm

The table above shows the descriptive statistics for the independent variable Trans.Size on each stock exchange list and on an aggregated level in the control period (Pre-Covid). Transaction size is calculated as the transaction size, in shares, in relation to the company's total number of shares outstanding, expressed in parts per million (ppm = 0.0001%). The data is comprised of 16,228 purchase transactions across all stock exchange lists.

Appendix C3. Descriptive Statistics Independent Variables - Covid (Treatment Period)

	Stock Exchange List									
	All		Large Cap		Mid Cap		Small Cap		First North	
Variable	N	%	N	%	N	%	N	%	N	%
Transaction Type	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
Purchases	10,980	*73%*	2,702	*71%*	1,874	*72%*	979	*78%*	5,425	*74%*
Sales	4,032	*27%*	1,124	*29%*	732	*28%*	273	*22%*	1,903	*26%*
Sector	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
Automobiles and Parts	164	*1%*	40	*1%*	84	*3%*	-	-	40	*1%*
Banks	335	*2%*	146	*4%*	189	*7%*	-	-	-	-
Basic Resources	408	*3%*	170	*4%*	58	*2%*	34	*3%*	146	*2%*
Chemicals	209	*1%*	-	-	-	-	-	-	209	*3%*
Construction and Materials	1,366	*9%*	699	*18%*	163	*6%*	159	*13%*	345	*5%*
Consumer Products and Services	706	*5%*	143	*4%*	210	*8%*	40	*3%*	313	*4%*
Energy	338	*2%*	8	*0%*	26	*1%*	15	*1%*	289	*4%*
Financial Services	415	*3%*	102	*3%*	132	*5%*	9	*1%*	172	*2%*
Food, Beverage and Tobacco	251	*2%*	29	*1%*	151	*6%*	-	-	71	*1%*
Health Care	2,073	*14%*	216	*6%*	470	*18%*	272	*22%*	1,115	*15%*
Household & Personal Products	34	*0%*	-	-	-	-	34	*3%*	-	-
Industrial Goods and Services	3,020	*20%*	798	*21%*	477	*18%*	228	*18%*	1,517	*21%*
Media	98	*1%*	-	-	38	*1%*	3	*0%*	57	*1%*
Personal Care, Drug and Grocery Stores	142	*1%*	17	*0%*	21	*1%*	-	-	104	*1%*
Real Estate	1,129	*8%*	482	*13%*	222	*9%*	-	-	425	*6%*
Retail	637	*4%*	230	*6%*	63	*2%*	2	*0%*	342	*5%*
Technology	2,601	*17%*	354	*9%*	185	*7%*	310	*25%*	1,752	*24%*
Telecommunications	690	*5%*	363	*9%*	23	*1%*	79	*6%*	225	*3%*
Travel and Leisure	349	*2%*	29	*1%*	94	*4%*	65	*5%*	161	*2%*
Utilities	47	*0%*	-	-	-	-	2	*0%*	45	*1%*
Insider Role	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
Non-material	10,109	*67%*	2,844	*74%*	1,750	*67%*	750	*60%*	4,765	*65%*
Material	4,903	*33%*	982	*26%*	856	*33%*	502	*40%*	2,563	*35%*
Report Period	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
No	11,422	*76%*	2,832	*74%*	1,800	*69%*	931	*74%*	5,859	*80%*
Yes	3,590	*24%*	994	*26%*	806	*31%*	321	*26%*	1,469	*20%*
Market Open	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
Closed	4,760	*32%*	1,107	*29%*	862	*33%*	424	*34%*	2,367	*32%*
Open	10,252	*68%*	2,719	*71%*	1,744	*67%*	828	*66%*	4,961	*68%*
Report Day	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
No	14,755	*98%*	3,769	*99%*	2,553	*98%*	1,228	*98%*	7,205	*98%*
Yes	257	*2%*	57	*1%*	53	*2%*	24	*2%*	123	*2%*
Relative	**15,012**	***100%***	**3,826**	***100%***	**2,606**	***100%***	**1,252**	***100%***	**7,328**	***100%***
No	10,257	*68%*	2,764	*72%*	1,982	*76%*	940	*75%*	4,571	*62%*
Yes	4,755	*32%*	1,062	*28%*	624	*24%*	312	*25%*	2,757	*38%*

The table above represents descriptive statistics across Stock Exchange Lists for the independent dummy variables covering all transaction in the treatment period (Covid), covering in total 15,012 transactions. "-" indicates that there is no transaction for that particular combination of variables.

Appendix C4. Descriptive Statistics Independent Variable: Trans.Size - Pre-Covid (Control Period)

Stock Exchange List	N	Mean	Median	Std. Dev.	Min	Max
All	**15,012**	**7 ppm**	**0.09 ppm**	**53 ppm**	**~ 0 ppm**	**5,703 ppm**
Large Cap	3,826	5 ppm	0.01 ppm	50 ppm	~ 0 ppm	1,412 ppm
Mid Cap	2,606	2 ppm	0.07 ppm	18 ppm	~ 0 ppm	474 ppm
Small Cap	1,252	5 ppm	0.20 ppm	31 ppm	~ 0 ppm	595 ppm
First North	7,328	11 ppm	0.16 ppm	79 ppm	~ 0 ppm	5,703 ppm

The table above shows the descriptive statistics for the independent variable Trans.Size on each stock exchange list and on an aggregated level in the treatment period (Covid). Transaction size is calculated as the transaction size, in shares, in relation to the company's total number of shares outstanding, expressed in parts per million (ppm = 0.0001%). The data is comprised of 15,012 purchase transactions across all stock exchange lists.

Appendix D: Correlation Matrix Broad Control Variable Group

Appendix D. Correlation Matrix and VIF-analysis of All Numeric Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(1) period.treatment	1.00																								
(2) incentive.program.log	(0.06)	1.00																							
(3) insider.rep.date.log	0.02	(0.03)	1.00																						
(4) insider.role.adj.board.member	(0.02)	(0.14)	(0.02)	1.00																					
(5) insider.role.adj.c.suite	0.10	0.29	(0.01)	(0.37)	1.00																				
(6) insider.role.adj.ceo	(0.04)	(0.05)	0.01	(0.36)	(0.21)	1.00																			
(7) insider.role.adj.cfo	0.02	(0.02)	0.03	(0.21)	(0.12)	(0.12)	1.00																		
(8) insider.role.adj.chairman	0.14	(0.07)	0.00	(0.21)	(0.12)	(0.12)	(0.07)	1.00																	
(9) insider.role.adj.management.team	(0.15)	0.00	0.01	(0.30)	(0.18)	(0.17)	(0.10)	(0.10)	1.00																
(10) insider.role.adj.other	(0.01)	(0.02)	0.00	(0.08)	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)	1.00															
(11) insider.role.adj.related	(0.01)	(0.01)	0.01	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	0.00	1.00														
(12) mark.act.log	(0.02)	0.08	0.03	(0.02)	0.02	0.00	0.01	0.01	(0.01)	0.00	0.00	1.00													
(13) market.adj.fngm.cap	0.11	(0.18)	(0.02)	0.13	(0.16)	0.05	(0.03)	0.07	(0.12)	0.05	0.00	(0.04)	1.00												
(14) market.adj.large.cap	(0.06)	0.28	(0.01)	(0.05)	0.23	(0.13)	(0.03)	(0.03)	0.02	(0.04)	(0.01)	0.05	(0.55)	1.00											
(15) market.adj.mid.cap	(0.05)	(0.06)	0.02	(0.08)	(0.03)	0.04	0.05	(0.03)	0.11	(0.02)	0.01	0.01	(0.42)	(0.31)	1.00										
(16) market.adj.small.cap	(0.03)	(0.04)	0.01	(0.03)	(0.05)	0.06	0.03	(0.03)	0.03	0.01	(0.01)	(0.03)	(0.28)	(0.20)	(0.16)	1.00									
(17) pub.date.month.1	(0.10)	(0.02)	(0.03)	0.03	0.01	(0.01)	(0.01)	(0.03)	(0.02)	0.00	(0.01)	(0.01)	0.06	(0.03)	(0.02)	(0.02)	1.00								
(18) pub.date.month.10	(0.01)	(0.05)	0.02	0.00	(0.04)	0.01	(0.01)	0.09	(0.03)	0.01	0.00	(0.04)	0.06	(0.03)	(0.01)	(0.05)	(0.06)	1.00							
(19) pub.date.month.11	0.00	0.02	0.04	(0.01)	(0.01)	(0.01)	0.00	0.07	0.00	(0.01)	0.01	0.04	(0.03)	0.04	(0.01)	0.01	(0.08)	(0.10)	1.00						
(20) pub.date.month.12	0.00	(0.05)	(0.04)	0.00	(0.04)	0.01	0.01	0.05	0.01	(0.02)	(0.01)	(0.01)	0.06	(0.08)	(0.01)	0.03	(0.07)	(0.09)	(0.11)	1.00					
(21) pub.date.month.2	0.01	0.05	(0.03)	(0.01)	0.03	0.00	(0.01)	(0.03)	0.01	(0.01)	0.01	0.02	(0.11)	0.10	(0.01)	0.04	(0.07)	(0.09)	(0.11)	(0.10)	1.00				
(22) pub.date.month.3	0.12	(0.08)	(0.02)	0.08	(0.05)	(0.01)	(0.02)	(0.02)	(0.02)	0.01	0.00	0.01	0.05	(0.05)	0.00	(0.01)	(0.08)	(0.10)	(0.12)	(0.11)	(0.11)	1.00			
(23) pub.date.month.4	0.00	0.03	0.06	0.01	0.02	(0.01)	0.00	(0.02)	0.00	0.02	0.02	(0.01)	0.00	0.02	(0.03)	0.01	(0.05)	(0.06)	(0.08)	(0.07)	(0.07)	(0.08)	1.00		
(24) pub.date.month.5	(0.03)	0.11	(0.01)	(0.06)	0.07	(0.02)	0.01	(0.03)	0.04	(0.01)	0.00	0.01	(0.10)	0.10	0.02	(0.02)	(0.08)	(0.11)	(0.13)	(0.12)	(0.11)	(0.13)	(0.08)	1.00	
(25) pub.date.month.6	0.03	0.01	(0.04)	(0.02)	0.03	(0.01)	0.01	(0.03)	0.02	0.01	(0.01)	(0.03)	0.03	(0.05)	0.02	0.00	(0.07)	(0.09)	(0.11)	(0.10)	(0.10)	(0.11)	(0.07)	(0.12)	1.00
(26) pub.date.month.7	0.02	(0.03)	0.03	0.01	(0.01)	0.02	(0.01)	(0.01)	(0.01)	0.01	0.00	(0.01)	0.03	(0.04)	0.01	0.00	(0.06)	(0.07)	(0.09)	(0.08)	(0.08)	(0.09)	(0.06)	(0.10)	(0.08)
(27) pub.date.month.8	(0.04)	0.06	0.06	0.01	0.03	(0.02)	0.02	(0.02)	(0.02)	0.00	(0.01)	(0.02)	(0.03)	0.07	(0.04)	0.00	(0.06)	(0.08)	(0.10)	(0.09)	(0.09)	(0.10)	(0.06)	(0.11)	(0.09)
(28) pub.date.month.9	(0.02)	(0.06)	(0.03)	(0.01)	(0.03)	0.06	0.00	(0.02)	0.01	0.00	0.00	0.02	0.01	(0.07)	0.06	0.01	(0.07)	(0.09)	(0.11)	(0.10)	(0.09)	(0.11)	(0.07)	(0.12)	(0.10)
(29) relative.log	0.06	(0.17)	(0.04)	0.30	(0.20)	(0.07)	(0.10)	0.14	(0.15)	(0.03)	0.03	(0.01)	0.15	(0.08)	(0.08)	(0.02)	0.00	0.09	0.04	0.02	(0.02)	0.06	(0.02)	(0.08)	(0.03)
(30) report.period.log	0.01	(0.04)	0.22	(0.03)	(0.02)	0.04	0.04	(0.03)	0.00	0.00	0.01	(0.01)	(0.08)	(0.01)	0.10	0.01	(0.12)	0.08	0.11	(0.14)	(0.10)	(0.03)	0.13	0.09	(0.15)
(31) sector.basic.materials	(0.01)	(0.04)	0.01	0.02	(0.04)	(0.01)	0.01	(0.01)	0.03	(0.01)	0.00	(0.05)	0.03	0.04	(0.07)	(0.01)	0.01	0.05	(0.03)	0.00	0.02	0.01	(0.01)	(0.01)	0.01
(32) sector.consumer.goods	0.01	(0.04)	0.00	0.00	(0.03)	0.07	(0.01)	(0.01)	(0.02)	(0.01)	0.01	0.00	0.01	(0.06)	0.09	(0.05)	(0.02)	0.01	0.02	(0.02)	(0.01)	(0.02)	0.01	0.03	(0.02)
(33) sector.consumer.services	0.00	(0.06)	0.02	(0.03)	0.00	0.02	0.01	(0.01)	0.02	0.02	0.00	(0.02)	(0.03)	(0.05)	0.09	0.01	(0.02)	0.02	0.02	(0.01)	0.00	(0.01)	0.00	(0.01)	0.00
(34) sector.energy	0.01	(0.03)	(0.01)	0.01	(0.03)	0.00	(0.01)	0.01	0.03	0.00	0.00	(0.05)	0.12	(0.07)	(0.05)	(0.02)	(0.01)	(0.01)	(0.03)	0.04	(0.02)	0.00	0.06	(0.03)	0.02
(35) sector.financials	0.01	(0.04)	0.00	(0.03)	0.03	(0.01)	0.01	0.02	0.01	(0.02)	(0.01)	0.01	(0.11)	0.06	0.11	(0.05)	(0.01)	0.03	0.01	0.01	0.00	(0.01)	0.02	(0.01)	(0.02)
(36) sector.health.care	(0.07)	(0.08)	0.00	0.01	(0.08)	0.06	0.03	0.02	(0.02)	(0.02)	(0.01)	0.03	0.06	(0.18)	0.12	0.02	0.03	(0.02)	(0.03)	0.03	(0.04)	(0.01)	(0.01)	(0.01)	0.00
(37) sector.industrials	(0.01)	0.13	(0.01)	0.06	0.09	(0.09)	(0.03)	(0.10)	(0.01)	0.05	(0.01)	0.06	(0.12)	0.19	(0.06)	0.00	0.00	(0.04)	(0.01)	(0.06)	0.03	0.07	(0.01)	0.04	0.01
(38) sector.real.estate	0.05	(0.07)	(0.01)	0.00	(0.05)	0.03	0.00	0.01	0.00	(0.02)	0.01	(0.01)	(0.09)	0.12	0.03	(0.08)	0.01	(0.03)	(0.01)	0.04	(0.01)	0.03	0.01	(0.03)	0.01
(39) sector.technology	0.05	(0.08)	0.00	(0.02)	(0.05)	0.01	0.00	0.12	0.00	(0.02)	0.01	(0.06)	0.21	(0.18)	(0.12)	0.09	0.01	0.04	0.05	0.02	(0.01)	(0.05)	(0.04)	(0.05)	0.01
(40) sector.telecommunications	(0.02)	0.28	0.01	(0.04)	0.13	(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)	0.05	(0.06)	0.16	(0.10)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	0.03	(0.03)	0.04	0.07	(0.04)
(41) sector.utilities	0.01	(0.01)	(0.01)	(0.02)	(0.02)	0.06	0.01	(0.01)	(0.01)	(0.01)	0.00	(0.01)	0.04	(0.03)	(0.03)	0.02	0.01	(0.01)	0.01	0.00	0.00	(0.02)	0.00	0.00	0.01
(42) trans.of.company	0.00	0.02	0.00	(0.01)	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	(0.01)	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00
(43) transaction.type.log	0.02	0.00	(0.04)	(0.06)	0.07	0.02	(0.04)	(0.07)	0.07	(0.01)	0.01	(0.08)	(0.01)	(0.02)	0.04	(0.01)	0.01	(0.04)	(0.05)	(0.03)	(0.01)	0.05	(0.02)	0.03	0.00
(44) weekday.fri	(0.01)	(0.04)	0.03	0.00	(0.02)	0.00	0.02	(0.02)	0.02	0.00	(0.01)	0.07	0.00	(0.02)	0.00	0.02	(0.02)	0.04	(0.02)	0.00	0.04	0.00	(0.01)	(0.01)	(0.03)
(45) weekday.mon	(0.01)	0.03	(0.04)	(0.02)	0.01	0.04	(0.01)	(0.02)	(0.01)	(0.02)	0.00	0.04	(0.04)	(0.02)	0.06	0.01	0.02	(0.01)	0.00	(0.01)	(0.03)	0.00	0.02	(0.02)	0.02
(46) weekday.sat	0.01	(0.02)	(0.02)	0.00	(0.01)	0.00	0.00	0.01	0.00	0.01	0.01	(0.23)	0.02	(0.03)	0.00	0.01	(0.01)	(0.01)	0.00	0.04	(0.01)	0.01	0.01	(0.02)	0.00
(47) weekday.sun	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	0.00	0.00	0.01	0.02	0.01	0.00	(0.25)	0.03	(0.04)	(0.01)	0.02	0.02	(0.01)	(0.01)	0.04	(0.02)	(0.01)	0.00	(0.01)	0.00
(48) weekday.thu	0.03	0.01	0.03	0.01	(0.01)	(0.02)	0.00	0.05	(0.01)	(0.01)	0.01	0.06	0.00	0.03	(0.01)	(0.02)	0.00	(0.04)	0.07	0.00	(0.01)	0.02	0.01	(0.02)	0.00
(49) weekday.tue	(0.02)	0.00	(0.01)	(0.02)	0.01	0.01	0.01	(0.01)	0.00	0.03	0.01	0.01	0.02	0.00	(0.02)	(0.02)	0.00	0.05	(0.02)	(0.02)	0.00	(0.02)	(0.01)	0.01	0.02
(50) weekday.wed	0.01	0.02	0.01	0.04	0.02	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	0.00	(0.01)	0.03	(0.02)	0.00	(0.01)	(0.03)	(0.02)	0.00	0.02	0.00	(0.01)	0.05	(0.01)

	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)	VIF
(1) period.treatment																										1.12
(2) incentive.program.log																										1.29
(3) insider.rep.date.log																										1.07
(4) insider.role.adj.board.member																										-
(5) insider.role.adj.c.suite																										-
(6) insider.role.adj.ceo																										-
(7) insider.role.adj.cfo																										-
(8) insider.role.adj.chairman																										-
(9) insider.role.adj.management.team																										-
(10) insider.role.adj.other																										-
(11) insider.role.adj.related																										-
(12) mark.act.log																										1.17
(13) market.adj.fngm.cap																										-
(14) market.adj.large.cap																										-
(15) market.adj.mid.cap																										-
(16) market.adj.small.cap																										-
(17) pub.date.month.1																										-
(18) pub.date.month.10																										-
(19) pub.date.month.11																										-
(20) pub.date.month.12																										-
(21) pub.date.month.2																										-
(22) pub.date.month.3																										-
(23) pub.date.month.4																										-
(24) pub.date.month.5																										-
(25) pub.date.month.6																										-
(26) pub.date.month.7	1.00																									-
(27) pub.date.month.8	(0.07)	1.00																								-
(28) pub.date.month.9	(0.08)	(0.09)	1.00																							-
(29) relative.log	(0.01)	(0.05)	0.00	1.00																						1.24
(30) report.period.log	0.06	0.09	(0.02)	(0.05)	1.00																					1.21
(31) sector.basic.materials	(0.01)	(0.02)	(0.01)	(0.01)	0.03	1.00																				-
(32) sector.consumer.goods	0.04	0.00	(0.01)	0.06	0.06	(0.03)	1.00																			-
(33) sector.consumer.services	0.00	0.01	(0.01)	0.03	0.03	(0.08)	(0.06)	1.00																		-
(34) sector.energy	0.01	(0.02)	0.00	0.01	(0.03)	(0.03)	(0.02)	(0.06)	1.00																	-
(35) sector.financials	0.00	0.00	(0.02)	(0.01)	0.02	(0.05)	(0.04)	(0.09)	(0.03)	1.00																-
(36) sector.health.care	0.02	(0.04)	0.10	(0.05)	0.03	(0.09)	(0.07)	(0.17)	(0.07)	(0.10)	1.00															-
(37) sector.industrials	(0.02)	0.03	(0.05)	(0.01)	(0.06)	(0.14)	(0.10)	(0.25)	(0.10)	(0.15)	(0.29)	1.00														-
(38) sector.real.estate	(0.01)	(0.02)	0.01	0.04	0.00	(0.06)	(0.04)	(0.10)	(0.04)	(0.06)	(0.11)	(0.17)	1.00													-
(39) sector.technology	(0.01)	0.01	0.00	0.04	(0.02)	(0.09)	(0.07)	(0.16)	(0.06)	(0.10)	(0.19)	(0.28)	(0.11)	1.00												-
(40) sector.telecommunications	(0.01)	0.03	(0.02)	(0.09)	0.00	(0.05)	(0.04)	(0.09)	(0.03)	(0.05)	(0.10)	(0.15)	(0.06)	(0.10)	1.00											-
(41) sector.utilities	0.03	(0.02)	0.00	0.04	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	1.00										-
(42) trans.of.company	0.00	0.00	0.00	0.01	(0.01)	0.00	0.00	0.00	0.00	0.00	(0.01)	0.00	0.02	0.00	0.00	0.00	1.00									1.00
(43) transaction.type.log	0.00	(0.02)	0.06	0.06	(0.03)	(0.01)	0.03	0.03	0.06	(0.01)	(0.01)	(0.03)	(0.05)	0.00	0.02	0.03	(0.01)	1.00								1.06
(44) weekday.fri	0.02	0.00	(0.01)	0.00	0.02	0.04	0.01	(0.01)	(0.01)	0.02	(0.01)	(0.01)	(0.01)	0.01	(0.02)	(0.01)	(0.01)	(0.04)	1.00							-
(45) weekday.mon	(0.01)	(0.01)	0.05	(0.02)	0.05	0.00	(0.01)	0.02	0.02	0.00	0.03	(0.04)	0.00	(0.02)	0.02	0.01	(0.01)	0.01	(0.24)	1.00						-
(46) weekday.sat	0.00	(0.01)	0.00	(0.03)	0.00	0.00	0.00	0.00	0.01	(0.01)	(0.01)	0.00	0.03	0.01	(0.01)	0.01	0.00	0.00	(0.07)	(0.07)	1.00					-
(47) weekday.sun	0.02	0.00	(0.01)	(0.02)	0.00	0.00	(0.01)	0.01	0.00	(0.01)	0.02	(0.03)	0.00	0.02	(0.02)	0.01	0.00	0.00	(0.08)	(0.08)	(0.02)	1.00				-
(48) weekday.thu	0.01	(0.02)	(0.03)	0.04	(0.03)	(0.01)	0.00	(0.02)	0.00	0.02	(0.03)	0.03	0.00	0.02	(0.02)	(0.02)	0.01	0.00	(0.24)	(0.24)	(0.07)	(0.08)	1.00			-
(49) weekday.tue	(0.02)	0.01	0.00	0.00	(0.02)	(0.01)	(0.01)	0.02	(0.01)	(0.01)	(0.01)	0.01	0.00	0.00	0.01	0.02	0.00	(0.01)	(0.23)	(0.23)	(0.07)	(0.08)	(0.23)	1.00		-
(50) weekday.wed	(0.01)	0.02	(0.01)	0.01	(0.03)	(0.02)	0.01	(0.01)	0.00	(0.02)	0.01	0.03	(0.01)	(0.02)	0.01	(0.01)	0.01	0.02	(0.24)	(0.24)	(0.07)	(0.08)	(0.24)	(0.23)	1.00	-

The table reports the correlation of each numerical variable available in our complete data set, i.e. both continous variables and dummy variables. The analysis has been run on the complete data set of 31,233 PDMR transactions. A VIF-value of "-" indicates that a VIF-analysis was not possible to run for the variable. That is due to the fact that it is part of a dummy variable group that has perfect negative correlation with each other.