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To Benefit from Uncertainty

A study on insider transactions during COVID-19

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Abstract

Research suggests that increasing R&D activities and uncertainty amplify market reactions following corporate news. We analyze insider transactions in biotechnological, life sciences and pharmaceutical companies listed on the NYSE, AMEX and Nasdaq during COVID-19. Cumulative abnormal returns are investigated with an event study following the filings of insider trades during times of uncertainty. We find that the market reacts stronger to insider transactions during COVID-19 compared to normal times. Additionally, we find that purchase transactions, compared to sales transactions, are perceived as more informative to market investors. Our evidence partly suggests that the insider's position affects the trade's signaling value to outsiders.

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1. Introduction

1.1 Background

As of December 4, 2022, the SARS-CoV-2 – commonly known as the COVID-19 pandemic – accounted for 6,6 million deaths globally (WHO, 2022). The World Health Organization (2020) declared the outbreak a public health emergency of international concern on January 30, 2020. Shortly thereafter, on March 11, 2020 the virus was declared an official pandemic. Restrictions were imposed and the S&P 500, a stock index consisting of the 500 largest listed companies in the United States based on market capitalization, plunged by 30%. The index had, a week before WHO's announcement on February 19, 2020 reached an all-time high at the time (Nasdaq, 2022). Yet, over the following two years that the pandemic would last, the S&P 500 would reach consecutive all-time highs. The healthcare companies constituting the index were no exception, yielding a return of 38% at its peak during the pandemic (S&P Dow Jones, 2022).

COVID-19 took its toll on the U.S. healthcare system, resulting in an immense workload on the workers, a medical supply shortage, and an increasing demand for a vaccine to end the pandemic (FDA, 2022). In the short term, the biotechnological, life sciences, and pharmaceutical companies needed to scale up to supply the growing demand. In the long run, they needed to develop new therapeutics to lead humanity on the critical path to normal times on the other side of the pandemic (Agrawal et al., 2020). The accuracy of tests and safety of vaccines became a spotlight for the media to investigate heavily. With increased government funding, cross-sectional cooperation, and an FDA clinical-trial fast track, the biotech, life sciences, and pharmaceutical industries developed and supplied vaccines in record times (Lo, 2021). During 2022 the biotech industry raised $35 bn in funds globally, doubling the figures from 2020 to shift the industry towards an innovative future (Berghauser Pont et al., 2022). The investment trend during COVID-19 also showed an increase of 25% in M&A deals in the biopharma sector during 2021, compared to pre-COVID (Berghauser Pont et al., 2022).

All corporate investments contribute to information asymmetry since managers can observe the investment's success continuously, while outsiders only obtain aggregate information at specific points in time (Aboody & Lev, 2002). R&D investments increase the information asymmetry between insiders and outside investors, even more than investments in tangible and financial assets (Aboody & Lev, 2002). One reason is that most financial and tangible assets are presented systematically and periodically through the financial statements, informing investors about changes in value (Aboody & Lev, 2002). However, the R&D items in the financial statements are more ambiguous. A company can partly capitalize on R&D activities, but the financial reports will not show the full picture of the research and development's value and productivity. Another reason that R&D further contributes to information asymmetry is the lack of organized markets. Investors can derive much information from prices regarding their firm-level value for financial and tangible assets.[1] Research and development results as well as successes are difficult to measure, and no asset prices exist to derive information from. Empirical evidence shows that the number of financial analysts following firms is significantly larger for R&D-intensive firms, presumably due to the undisclosed information surrounding R&D activities (Barth et al., 2001). The positive relationship between analysts and R&D intensity is argued by Tasker (1998) to display the increased demand from market investors for valuable information. This information asymmetry and high demand for information shed light on insiders within R&D-intensive firms who can exploit their private information for stock trading.

Insider trading is often associated with illegal trading and corporate scandals. For example, Raj Rajaratnam, a hedge fund Galleon Group manager, was convicted for one of the largest insider trading prosecutions. The government estimated that Rajaratnam profited 63 million dollars from insider trading (Duignan, 2022). However, most insider trading is conducted in a legal manner. In 1998, 87 countries worldwide had established regulations for insiders to trade on private information (Bhattacharya & Daouk, 2002). In the U.S., illegal insider trading is defined as the trading of a company's securities by individuals who have access to non-public information about the company. An insider can be an officer, director, shareholder of at least 10%, or anyone that possesses private information because of their relationship to the company. The act of an insider taking advantage of this information is considered a breach of the individual's fiduciary duty. Companies are therefore required to report trading by corporate insiders to the Securities and Exchange Commission (SEC).

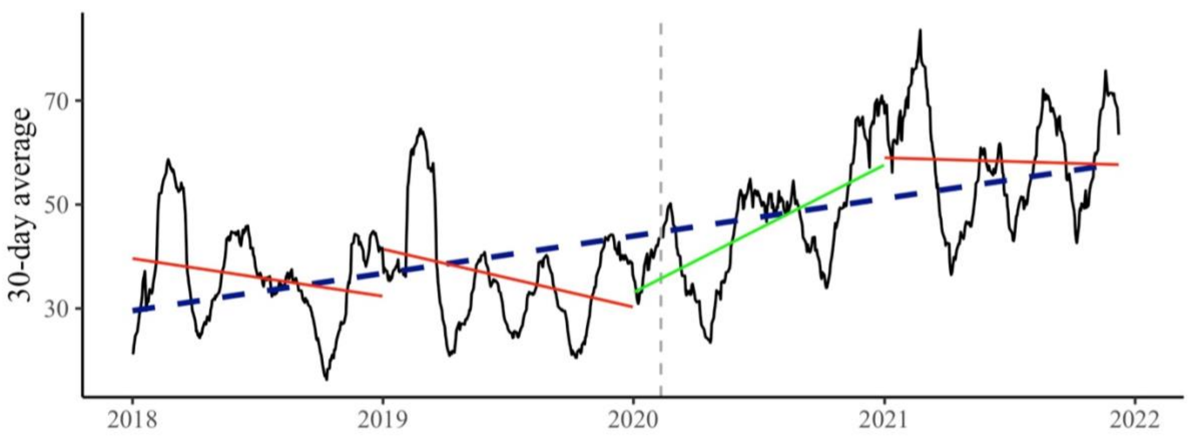
While insider trading occurs in all industries, healthcare companies conducting clinical trials are particularly prone to this due to the information asymmetry related to their R&D. SEC has enforced special prosecutions in the healthcare and life sciences industries in the U.S. (Fischer et al., 2021). Companies within the healthcare industry often develop new treatments or technologies in research projects. The news concerning important events, such as FDA approval

[1] E.g. a change in commodity prices would be displayed as a change in, for instance, the value of inventory.

or clinical trial success, can yield large market reactions due to the immense potential for traders' financial gain. For instance, the SEC filed charges against Mohammed A. Bari in May 2021, a medical investigator working for Karuna Therapeutics. The charges covered the clinical trial of KarXT, a drug brought forward to treat Schizophrenia (SEC, 2021). Bari had been informed that the clinical results were promising, which was considered confidential information. Bari bought shares before the clinical results were announced, resulting in him earning a return of 340% (SEC, 2021). While media scandals often include extreme cases of market reactions, Singh and Rocafort (2022) instead show that the market reaction following positive clinical trial results yields an average cumulative abnormal return of 6,35%. Trading based on positive clinical outcomes would thus yield moderate returns compared to Bari's trading.

Insider trading activity within the healthcare industry (defined as the biotech, life sciences and pharmaceutical industries) increased during COVID-19, which can be seen in figure 1. Initially during 2020 Q1 the number of trades dropped, but increased thereafter resulting in 2020 being the only year showing a positive trend. The seasonal pattern can best be described by the SEC restrictions prior to releases of financial statements.

Figure 1: Insider trading frequency



Note: The graph reports the frequency of monthly insider transactions within the biotech, life sciences, and pharmaceutical industries during 2018-2022 as a 30-day rolling average. The dashed blue line is a trend line for the entire period, while the green (red) lines display a positive (negative) yearly trend. The vertical grey dashed line indicates the start of COVID-19, based on WHO's announcement on March 11, 2020.
(WRDS, 2022)

Aboody and Lev (2002) assume that officers and directors are priori to having R&D-related information. Hence, acquiring such information is costly for outsiders, as it requires significant investment in scientific knowledge and time, for instance, to analyze financial reports and continuously follow clinical trial development. They argue that the cost of acquiring valuable information varies positively with R&D intensity. Therefore, retrieving and incorporating all relevant insider information about a company and a sector is infeasible. Outside investors can, at a lower cost, use the SEC database reporting insider trades to observe the trading habits of insiders and implement this into their trading strategies.

1.2 Past literature

Previous literature has found that insiders benefit from private information and yield financial gains through purchase and sales transactions (Lakonishok & Lee, 2001; Tavakoli et al., 2012). Furthermore, it is established that insiders can predict market movements and time the market (Lakonishok & Lee, 2001). The previous research shows positive abnormal returns following purchase transactions and negative returns following sales transactions (Lakonishok & Lee, 2001; Tavakoli et al., 2012; Lee et al., 1992). Market reactions subsequent to insider transactions showed a positive correlation with R&D activities (Aboody & Lev, 2002). During times of uncertainty, outside investors rely more upon provided information that is believed to originate from informed parties (Loh & Stulz, 2018).

1.3 Purpose

This study aims to test the market reaction to insider transactions within the healthcare industry during the uncertain time of COVID-19. The healthcare industry in this study is limited to the biotech, life sciences, and pharmaceutical industries. We look at the market reaction following insider transactions and further analyze this dependent on transaction characteristics, i.e., purchase and sales, and insider job roles. This is done by measuring stock market reaction based on cumulative abnormal returns over the following two trading days from when the insider transaction was reported. We study the reporting day, which is when the transaction is publicly available to outside investors, and not the actual transaction day. Due to data limitations, we assume that the reporting of a trade occurred at the start of each trading day. We conduct t-tests, OLS panel regressions, and a difference-in-differences tests to measure the change in stock market reaction during the SARS-CoV-2 pandemic. To the best of our knowledge, stock market reaction following insider trades has not previously been examined in detail with the aspect of the uncertainty during COVID-19 in industries with heavy research and development activities.

1.4 Research Questions

This paper aims to answer the following research questions:

Research question 1: *Did the effect of insider transactions on market reactions change during COVID-19?*

Research question 2: *Which transaction type was perceived as the more informative by the stock market during COVID-19, during COVID-19?*

Research Question 3: *Is the perceived informativeness by the stock market of an inside transaction affected by insiders' position within the company, during COVID-19?*

1.5 Contributions

No literature that crossed us has investigated the market reactions of insider trading within the R&D-heavy healthcare industry during COVID-19 (2020Q1-2022Q4), a period with high market uncertainty compared to a period with lower market uncertainty (2018Q1-2019Q4). Our contribution is, thus, investigating the influence of insider transactions on market reactions in the healthcare industry during the uncertain time of COVID-19. The pandemic is a relatively unexplored research topic compared to other periods of crisis. Our study also aims to add more evidence to the literature on market reactions, especially with regard to insiders, different transaction characteristics and job roles.

1.6 Summary of Results

The results show that market reactions to insider trades within the healthcare industry increased during COVID-19. We observed even higher market reactions for purchases and for some transactions conducted by insiders of more influential job roles. The abnormal market reaction increased by 2.42% for purchases and decreased by 0.24% for sales (p-value<0.01). Purchases of *Directors* at 3.4% and sales for *Others* at 0.87% (p-value<0.01) show the highest market reaction amplitude. The results of the t-test and the linear OLS panel regression mostly align with each other. The regression model is better at isolating the effect from insiders during uncertainty. Further, our difference-in-differences test also shows that the market reactions were significantly higher during COVID-19 for insider purchases within the healthcare industry compared to the S&P 500. More extensive results will be provided in section 4.

1.7 Disposition

This thesis is structured into six sections; the second section reviews previous literature and develops our hypotheses. Section 3 explains our method, including our tests and sample selection. Section 4 displays our results, which are thereafter analyzed in section 5. Lastly, section 6 consists of concluding remarks touching upon limitations and future research.

2. Literature Review and Theory

The following section will give insight into previous research relevant to our thesis. We will start by explaining the Efficient Market Hypothesis and critique against it. Afterward, we present previous literature on insider transactions in different contexts. Thereafter, we present empirical evidence on signaling theory concerning how outside investors value signals. Lastly, based on previous research, we develop our hypotheses.

2.1 Market Efficiency

Fama (1970) defined the stock market to be efficient if the stock is priced based on all available information. The study determined three levels of market efficiencies: *strong*, *semi-strong*, and *weak*. *Strong* describes a market where all non-public and public information are correctly and directly reflected in the stock's price. *Semi* describes a market where only public information, for instance, annual report and news, is accurately and directly reflected in the stock's price. Lastly, *weak* defines a market where the stock price only reflects historical information. The Efficient Market Hypothesis explains that the difference in assets' expected returns is proportionate to the risk undertaken by the investor.

Critique against the Efficient Market Hypothesis

The Efficient Market Hypothesis builds on the assumptions that all investors are rational, and all deviations are independent for each investor, canceling out on an aggregate level. This implies that no arbitrage opportunities exist. However, abnormal returns occur and are defined as the difference in an asset's return and its expected return. Shiller (1984) brought evidence which showed that social movements and human nature heavily influence stock prices. His findings showed that trends are unpredictable and ordinary investors might overreact to news announcements of future dividends earnings. This makes the demand of investors unpredictable, which in turn affects stock prices. Black (1986) argued that markets are inefficient due to noise and further defined noise as the opposite of information, i.e., inaccurate data and information. Noise causes markets to be inefficient and inaccurate, but it is still vital for existing markets to function. In each specific trade, there is always a loser and a winner. Black (1986), furthermore, argued that if investors acted rationally, the losing party would not undertake the trade. Hence, only a few trades on the market would be completed without the existence of noise. Related to the field of psychological behavior in financial markets, De Bondt and Thaler (1987) suggested that investors tend to overreact to unexpected and dramatic news. Their study found that portfolios consisting of prior losers outperform prior winners by about 25% three years after portfolio formation despite the portfolio consisting of previous winners being significantly riskier, during the formation period, than the loser portfolio.

2.2 Insider Trading

Insider trading involves trading upon the information asymmetry between the insider and an outside investor. Credible and lawful information that beats the market is highly demanded by market investors and hence, yields significant stock market reactions.

Informativeness of insider transactions

Iqbal and Shetty (2002) examined the possible causal relationship between insider transactions and stock market returns. They studied insider trading around a firm-specific event, excluding specific corporate events, with a time-series relation between monthly insider trades and returns. For 60% of their sample firms, they observed a positive relationship between insider transactions and future stock returns. However, they find that the causality is stronger from stock returns to insider transactions than from insider transactions to stock returns. Seyhun and Bradly (1997) studied insider trades around corporate bankruptcies to determine if insider trade to avoid capital losses. Their findings partly contradict Iqbal and Shetty (2002) as they found a significant amount of insider sales prior to the filing date of the bankruptcy. Moreover, top executives and officers sell more intensely compared to other insiders. Their study found that insiders sell ahead of a dip and buy after the fall. Their model is unique, as they looked at insider transactions several years prior to the event day. They found that insider selling commences five years before the bankruptcy was filed and consequently aggregates up until the announcement month. Chowdhury et al. (1993) studied the relationship between insider transactions and stock market returns through an autoregressive model and found that insiders hold predictive content, but only to a small extent. They also found that the degree of mispricing that insiders can detect is small. Moreover, the following insiders' trades, as a result of the mispricing, are not significantly associated with unexpected macroeconomic factors. Still, outside investors are unable to predict future market returns by following insiders' trades.

Previous literature includes studies of insider trading around various corporate news and events to determine if insider trading yields significant stock market reactions and, thus, abnormal returns. Karpoff and Lee (1991) presented evidence that insiders trade around important corporate news announcements, such as stock and convertible debt issuance, to earn abnormal returns. They found that the prospect of legal and market penalties did not deter insiders from trading ahead of the announcements and showed that managers possess superior information that is benefitted from upon new equity issues. Lee et al. (1992) analyzed the relationship between stock repurchase announcements and managers' trading habits to see if it resulted in a personal gain for the insiders. Insiders increase their purchases and decrease their sales ahead of offers that do not follow take-over-related events. However, prior to offers that follow take-over-related events, only the number of insider sales decreased. Cheng and Davidson (2011) analyzed insider transactions as a proxy for information asymmetry. They studied good and bad news concerning earnings and dividends announcements and found that information asymmetry is larger for bad news than good news. The market reacted stronger to a decrease in earnings and dividends compared to an increase. Thus, they concluded that insider trades reduce information asymmetry to a larger extent prior to bad news. Lamba and Khan (1999) investigated whether insiders exploit their information ahead of exchange listings and delistings. In firms listing on the NYSE or AMEX exchange, they found that company insiders act upon personal information by purchasing or postponing the sale of shares. For firms about to delist, insiders sell their private stocks ahead of the event, resulting in abnormal returns. Overall, they conclude that insiders possess and act upon private information compared to outside investors.

Insider trading regulations

Some authors have criticized tighter regulations toward corporate insiders. Manne (1966) stated that if insiders are tolerated to trade on non-public information there will be incentives for them to create informational value for the company, which also favors society. He argued that insiders should be compensated if they create value for society. The rationale being that if insiders were to trade on non-public information, it would incentivize more corporations to pursue innovations. Fama (1970) also criticized tighter regulations, arguing that higher tolerance of insider trades would result in more accurately reflected prices of stocks in the market. The market would, as a result, shift from a *semi-strong* to a *strong* market as private information is reflected in the stock prices.

Thompson (1999), on the other hand, provided critique towards looser regulations of insider trading. Firstly, the compensation system has changed much since 1966 to align stakeholders' gain with corporation performance. Secondly, less regulation towards insider trading would not only incentivize insiders to pursue favorable actions in terms of research and be compensated for such projects. Painter (1999) argued that insiders would also pursue adverse activities for corporation performance and still benefit from such behavior with short selling (Painter, 1999). Painter (1999) argued that it is more reasonable to statute compensation systems where the stakeholder only is incentivized to act towards increased corporate performance. Furthermore, Kronman (1978) criticized the idea of entrepreneurs being compensated with the help of insider trading. Essentially, the innovator is not necessarily the one that will profit from the innovation. For instance, the scientists that contributed to a new cure in a medical corporation will most likely not be compensated. Thus, the problem of innovators not being fully compensated is not solved with looser regulations towards insider trading.

Insider transaction characteristics

There are two major approaches in previous research regarding which event day to choose when analyzing abnormal returns related to insider transactions. The first standard is to look at the trading day, i.e., when the insider conducts the transaction, which generally investigates the returns earned by insiders. The second standard is to examine returns around the reporting day of a transaction, which instead explores the market reaction. Previous research is inconclusive on whether insiders' purchases or sales of shares yield the highest market reactions.

Lakonishok and Lee (2001) studied insider trades and the market reaction on the U.S. stock markets between 1975-1995. They found that the cumulative abnormal return (CAR) from the trading day with an event window of five days was 0.59% and 0.17% for purchases and sales, respectively. Still, the results from the trading day were statistically insignificant. However, the results were significant with a 5-day event window from the reporting day. Purchases yielded a CAR of 0.13 %, while sales yielded -0.23 %. Chang and Suk (1998) studied insider returns from the reporting day on the U.S. stock markets between 1988 to 1990 and found a three-day

CAR of 0.33% for purchases and -0.44% for sales from the reporting day. Betzer and Theissen (2009) instead studied insider transactions on the German stock exchange between 2002 and 2004 and found that purchases yielded a CAR of 5.79% and sales of -5.40% during a 21-day event window from the trading day. Fidrmuc et al. (2006) studied the London Stock Exchange from 1991 to 1998 for market reactions to insider transactions. Studying all trades, they found CAR using a 5-day event window for purchase transactions that corresponded to 1.65%, while sales were 0.49%. For large trades, defined as exceeding 0.10% of the firm's market capitalization, market reactions for both transaction types were larger in magnitude compared to trades of all sizes. Purchases showed a CAR of 4.62% and purchases yielded a CAR of -0.53%. When studying a two-day event window, they found the same trend. On the other end, Friederich et al. (2002), who also studied the London Stock Exchange between 1986 and 1994 with a two-day event window, including the trading day, yielded a CAR for purchases of 0.42% and sales of -0.17%. Jeng et al. (2003) used a performance-evaluation study to calculate the abnormal returns earned by insiders. They found that insiders earn more than 6% per year in abnormal returns stemming from purchases, compared to sales which did not yield any significant abnormal returns. They argue that the regulatory system is sufficient and that outsiders overall are not put at a disadvantage when trading compared to insiders. Partly in line with this, Bajo and Petracci (2006) studied the Italian Stock Exchange (Borsa Italiana) between 1998-2002 and found that insider trades with a 10-day event window from the trading day yielded 3.18% and -3.67% CAR for purchases and sales respectively.

To summarize, the studies unanimously show that insiders earn abnormal returns. However, there seem to be tendencies of larger returns and market reactions for purchases, and the literature is still inconclusive regarding which transaction type yields the highest return.

Insider roles

Previous research tends to look at all insiders instead of dividing them into different job roles. However, it is not necessarily true that all insiders inside a company possess the same amount of information about the corporation. Some studies show that insiders with more influential roles are better at predicting the company's value and yield higher CAR than insiders with less influential positions.

Seyhun (1986) studied the CAR earned by insiders in the U.S. between 1975 and 1981 and categorized insiders into five groups. The results showed that insiders with higher decision-making power made greater returns. Degryse et al. (2009) tested insiders' returns in the Netherlands between 1999 and 2008 during a window of one and a half months after purchases and found abnormal returns from insiders of 2%. However, when separating the insider group into top executives and other insiders, the return was significantly higher for top executives and not substantially different from zero for other insiders. The study suggested that top executives are better informed than the rest of the insiders. In addition, Tavakoli et al. (2010) identified greater explanatory power for abnormal returns among directors regardless of firm size, while the explanatory power for officers was only found to be higher in small firms. Wang et al. (2012) used another approach, testing CAR of purchases for CEOs and CFOs between 1992 and 2002 over 12 months. They found that CFOs earn abnormal returns of 7.4% while CEOs only earn 2.4% yearly, with the reason identified as CFOs incorporating financial information into future earnings better than CEOs.

To conclude, previous research seems to agree that there is a difference in abnormal returns depending on the insider's position within the company. Higher-level job roles that are more influential tend to be associated with higher abnormal returns. However, the underlying reason for this is not mutually agreed upon by the literature. On the one hand, it is argued that they are indeed better informed. On the contrary, it is suggested that the market simply reacts greater to one group of insiders than the other due to higher signaling effects.

Insider trading and R&D

Literature touching upon insider trading in R&D-heavy and, more specifically, the healthcare industry is scarce. Coff and Lee (2003) explored insider trading to determine appropriate rent for R&D advancements and investments. Their findings showed that insider purchases generate larger positive stock market reactions for R&D-heavy firms, compared to companies with little R&D activities. Outside investors possibly assume that insiders use purchase and sales transactions to appropriate rent from R&D successes. Furthermore, Adooby and Lev (2002) focused on insider trading within R&D-heavy firms to determine whether it is a source of insider gains. They studied open market purchase and sales transactions conducted by executives, assumed to possess more information than company employees. They examined the association between insider gains and information asymmetry, proxied by the firms' R&D intensity. Their main findings concluded that insider gains in R&D-intensive firms are substantially larger when compared to firms with little R&D activities. They showed that this is partly due to insiders taking advantage of their knowledge of planned changes in R&D

budgets. They stated that R&D contributes to information asymmetry, hence, enhancing the reliance of outside investors on insider transactions. Their study pointed out the fact that outsiders are only able to obtain information about R&D developments at discrete points in time, such as clinical trial successes, investment productivity assessments and FDA approvals. Lastly, they found that insiders can time their transactions accordingly to the change in R&D expenditures, which is previously documented to generate investor reaction upon disclosure.

2.3 Stock Market Reactions during Uncertainty

Loh and Stulz (2018) studied whether the state of the economy in crisis and bad times affect the value of sell-side analysts' output for investors. They theorized that increased uncertainty affects the value of information. The value of analysts' output in bad times compared to good times was analyzed by using the two-day CAR capturing the market reaction. Bad times were identified as a crisis or recession using either various financial crises or a policy uncertainty index and an economic uncertainty index. Focusing on macro, not firm-specific, bad times allowed them to isolate the effect of macro shocks on the value of analysts' revisions, as the macroeconomic events are exogenous to the analysts. Loh and Stulz (2018) found that analysts' recommendations were more influential during uncertain times, as the stock-price impact was larger compared to normal times.

Kacsperczyk et al. (2017) showed that information about future payoffs, estimated by institutional ownership, contains higher informational value during times of uncertainty. Schmalz and Zhuk (2018) developed a model where some investors are uncertain if others trade based on information or noise. They found that uncertainty about other investors leads to a non-linear stock price that reacts asymmetrically to news, as stock prices are more sensitive to bad news than good ones. Market reactions were up to 70% larger to earnings news of firms in bad times when compared to good times. Additionally, they found that the stock market reaction varies with the belief of the signal's information quality. Higher quality signal and greater likelihood of the investor being informed decreased the risk and the expected return. Chiu et al. (2018) found that investors had more pessimistic sentiments during the financial crisis of 2008, which accelerated the reduction of equity liquidity, and consequently, intensified the net-selling pressure on investors.

2.4 Signaling Theory

Asset pricing models focus on uncertainty in a stock's fundamentals but assume that investors' trading characteristics are homogenous. Signaling theory within the field of accounting and finance origins from the information asymmetry between the firm’s management and outside investors. Yasar et al. (2020) investigated market reactions on the U.S. stock exchanges with regard to the value that investors put on signals. They argued that it is difficult for outside investors to differentiate between legitimate knowledge and market noise. In line with this, Schmalz and Zhuk (2018) stated that uninformed investors can assign probabilities of investors possessing valuable and high qualitative information. In our thesis, the stock market’s reaction is determined by the weight put on signals coming from insider transactions. Though, during uncertain times, the equilibriums change and filings of insider transactions may be interpreted and utilized to different extents by investors, possibly resulting in differing stock market reactions. Pastor and Veronesi (2009) examined how government policy changes affect stock prices. They stated that in a simple Bayesian model, the impact of new signals depends on the weight that the individual puts in the new signal and the weight put on the previous. The new signal’s precision increases relative to the uncertainty of past signals. Thus, if outside investors determine a positive trend of stock market returns of insider transactions, this would imply that their reaction increases in the future to similar signals. Veronesi (1999) found that stock markets overreact to bad news in good times and underreact to good news in bad times. During periods of high uncertainty, the expectations of future cash flows tend to react more swiftly to news. Higher sensitivity to news increases the share return volatility.

2.5 Conclusion of Previous Research

The literature agrees that insider transactions are followed by market reactions, consisting of market investors trying to reduce information asymmetry. Previous studies are inconclusive on which transaction type, purchase or sales, generate the largest abnormal returns. Furthermore, insiders can earn varying abnormal returns based on their position within the company. Lastly, during uncertain times investors overreact to news, as the value of the information is perceived as higher.

2.5. Hypotheses

In this section, based on previous research, we develop four hypotheses that are tested in a later section. The first, regards the overall effect of COVID-19 on market reactions. The second, concerns directions of change in abnormal returns for purchases and sales. Thirdly, we hypothesize which transaction type is perceived as the most informative, and lastly, how insider roles affect the perceived informativeness.

Hypothesis 1: *Insider transactions yield greater market reactions, during COVID-19.*

During times of uncertainty, we predict investors to become more reliant on insider information, i.e., insiders' trading will yield greater stock market reactions proxied by larger abnormal returns. Loh and Stulz (2018) found that analysts are more valuable in bad times because investors face challenges that they do not in good times, hence why they rely more on the analysts' output. The signals from analysts and insiders for investors could be used to diminish investment uncertainty. This could potentially result in an overreaction from market investors (De Bondt & Thaler, 1987). Loh and Stulz (2018) showed that the price impact of analysts' recommendations is greater during times of uncertainty compared to normal times. Additionally, Adooby and Lev (2002) found that stock market reactions from insider trades in R&D-intensive firms are substantially larger compared to firms with little R&D activity. Utilizing the findings in Kasperczyk et al. (2017); Chiu et al. (2018); Schamlz and Zhuk (2018), who found that the weight that outside investors put on corporate information increases during times of uncertainty, we argue that the healthcare industry will yield greater market reactions following the filing of insider transactions during COVID-19.

Hypothesis 2: *Purchase transactions yield positive abnormal returns, and sales transactions yield negative abnormal returns, during COVID-19.*

Hence, private knowledge about a firm contains positive and negative information, purchase and sales transactions represent positive and negative signals respectively. Following the findings from Coff and Lee (2003); Lakonishok and Lee (2001); Tavakoli et al. (2012); Bajo and Petracci (2006) and Fidrmuc (2006) who established negative and positive associated abnormal returns to sales and purchase transactions respectively when studying the market reaction from the reporting day, we argue this to be the case in our study. Similarly, Loh and Stulz (2018) studied analysts' sell and buy recommendations, and saw upgrades resulting in positive abnormal returns, and downgrades resulting in negative abnormal returns.

Hypothesis 3: *Insider purchase transactions will have a higher signaling effect than sales to outside investors, during COVID-19.*

The findings of Tavakoli et al. (2012) and Jeng et al. (2003) showed that purchases are perceived as more informative regarding future returns. This is observed as purchase transactions mainly occur ahead of upswings in the stock price, while smaller returns follow sales transactions. Lakonishok and Lee (2001) found that insiders sell equity for various reasons, indeterminable to outside investors. Instead of predicting a downturn, an inside investor may sell private shares for liquidity reasons or involvement in compensation programs. Hence, we argue that purchase transactions during times of uncertainty will yield higher stock market reactions, as the market expects an upswing. This will be seen by a larger magnitude of abnormal returns. However, for sales transactions, we expect the market to be uncertain about the reason for the transaction, thus yielding smaller abnormal returns. This is in accordance with Betzer and Theissen (2009), Fidrmuc et al. (2006) and Friedrich (2002). Furthermore, Coff and Lee's (2003) results strengthen this hypothesis. They found that investors mimicking management's insider purchases in R&D heavy firms, which the healthcare is argued to be, allow them financial benefits. The relationship for sales is smaller though, as sales present little new information and possibly reflect other personal motivations (Yermack & Ofek, 2000).

Hypothesis 4: *More operationally influential roles result in larger market reactions, during COVID-19.*

We expect that insiders that are more engaged in decision-making will yield bigger market returns, as we argue they possess more financial, managerial, and operational information. Consistent with Tavakoli et al. (2010), insiders with more senior positions will yield higher abnormal returns than insiders with lower-ranked jobs. This is in line with the results of Seyhun (1986), Degryse (2009), and Wang et al. (2012). Schamlz and Zhuk (2019). They found that outsiders cannot with certainty determine which outsiders possess significant information for financial gains. However, they found that the stock market reacts positively to higher perceived information quality. Higher executives are argued to receive information earlier and hold more operationally important information. Thus, increasing the probability that the investors see their transactions as more informative. This aligns with Seyhun (1986), who proved an information hierarchy hypothesis, which states that the information content of a transaction depends on how senior the trader is in the company.

3. Method

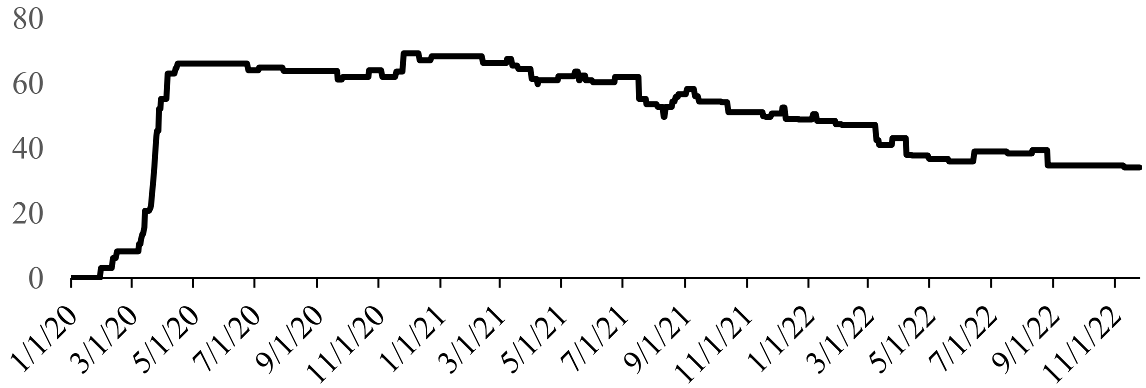
This study aims to analyze the stock market reaction to insider transactions during the uncertain times of the COVID-19 within the U.S. healthcare industry, which in this thesis is limited to the biotechnological, life sciences, and pharmaceutical industries. Following the methodology in Loh and Stulz (2018), we conducted a traditional event study comparing the independent variables before and during COVID-19, with a two-day event window from the reporting day of the inside transaction. In addition, this study also tests the effect of insiders' role within the company on the stock market reaction. This paper further implements insider transaction information from Lakonishok and Lee (2001) and Tavakoli et al. (2012). All data was gathered from CRSP, Compustat and Thomson/Refinitiv via the WRDS database during the autumn of 2022.

3.1 Research Design

The treatment period of COVID-19 is determined first in order to establish the control period that this study covers. To avoid possible seasonality affecting the results, as seen in figure 1, we decided to apply full calendar years as cut-off points for the control and treatment period. While following the same methodology of Loh and Stulz (2018), which determined periods of uncertainty using a policy uncertainty index and an economic uncertainty index, this paper instead utilizes the Oxford COVID-19 Government Response index to determine at which point the U.S. government initially imposed restrictive measures. The government response index is a proxy for societal, economic, and financial uncertainty. The start of the treatment period is determined by the first time the U.S. government response index, see figure 2, differed from zero, which is on February 3, 2020. Determining the end of the treatment period, based on the index, is ambiguous as it has until today not equaled zero. Instead, the closest year-end to Russia's invasion of Ukraine on February 24, 2022, marks the end of the treatment period to avoid further macroeconomic events affecting our results.

The treatment period is therefore defined as 2020-01-01 to 2022-01-01. The control period is determined based on the same number of calendar months as the treatment period (24). The control period is therefore defined as 2018-01-01 to 2019-12-31, i.e., 2018 Q1 to 2019 Q4.

Figure 2: U.S. government COVID-19 response index



Note: The graph shows the U.S. COVID-19 government response index, calculated over 23 indicators considering policies of containment/closures, economics, and the health system. (University of Oxford, 2022)

To test our hypotheses, this study applies abnormal returns to measure the stock market reaction, which aligns with Loh and Stulz (2018). The abnormal return is calculated in excess of the CRSP equally weighted NYSE, AMEX, and Nasdaq index from the share's daily return, identical to Seyhun (1998). Each insider transaction is matched with the respective abnormal return based on the date the insider transaction was reported to the SEC.

The insider transactions were divided into two subsets based on their transaction type (purchase and sales), displayed by their transaction code reported to the SEC.[2] These transactions were further divided into the subsets of *Directors*, *Officers*, *Shareholders*, and *Others* based on the insider's role in the company.

Finally, we conduct statistical t-tests for unequal variances, similar to Loh and Stulz (2018), on all the different subsets based on transaction type and job role, comparing the stock market reaction during the control and treatment period. Thereafter, an Ordinary Least Squares (OLS) regression is performed where the abnormal returns are predicted by an independent variable indicating if the insider transaction was reported during COVID-19 or the control period. The regression is conducted on an aggregate level, as well as on every subsample based on transaction type and the insider's position within the company. Unlike Loh and Stulz (2018) and Lakonishok and Lee (2001), we conduct a difference-in-differences test. This is a statistical method studying the differential effect of a specific treatment on a treatment group compared

[2] Transaction code "S" and "P" represents open market sale and purchases of the stock respectively.

to a control group (Angrist & Pischke, 2009). With this, we compare the abnormal returns of insider sales and purchases separately during the treatment and control period between the healthcare industry and the overall stock market, proxied by the S&P 500 companies as the control group.

3.1 Model

Following Loh and Stulz (2018), we measure the stock-price impact, thus, the perceived informativeness of insider transactions through the dependent variable cumulative abnormal return, which is the daily abnormal returns summed up over an event window. Identical to Seyhun (1998), the abnormal return is calculated by subtracting the daily equally weighted NYSE/AMEX/Nasdaq CRSP index return from the daily return of stock **i** on the reporting date **t**, which is defined as our event day. The reporting date is chosen, similar to Lakonishok and Lee (2001), as this is the date that the insider files the transaction to the SEC at which point the transaction is visible to market investors. Lakonishok and Lee (2001) implement a time lag from the reporting date to the event date **t,** as they argue it takes time from reporting the transaction to the SEC until it reaches market investors. Deviating from Lakonishok and Lee (2001), we do not incorporate such lag from the reporting date to the event date. Using the same rationale, we look at online databases that contain insider transactions like WRDS, CRSP, and DATAROMA, and do not observe a lag. Hence, we argue such lag is not relevant anymore. The daily return during the reporting date **t**, which is the event date (t_0), is calculated by subtracting the opening price $\mathbf{P^O}$ from the closing price $\mathbf{P^C}$ of security **i**.

<u>Abnormal return for companies conducting insider transactions.</u>

$$AR_{i,t} = \frac{P_{i,t}^{C} - P_{i,t}^{O}}{P_{i,t}^{O}} - R_{t,NYSE/AMEX/NASDAQ}$$

Where:

$P_{i,t}$ = The share price of company i, on date t

$R_{t,NYSE/AMEX/NASDAQ}$ = The NYSE/AMEX/Nasdaq index equally weighted return on date **t**

Moreover, the dependent variable, cumulative abnormal return CAR is calculated by summing up the abnormal returns $AR_{i,t}$ over the event window [0,1], i.e., the reporting date **t** and the next trading day. Thus, the event window is set to two days, identical to Loh and Stulz (2018).

Cumulative abnormal return in the event window

$$CAR_{i,t} = \sum_{t=0}^{1} AR_{i,t}$$

Where:

$AR_{i,t}$ = The abnormal return for the share of company **i** during the day **t**.

$CAR_{i,t}$ = The cumulative abnormal return of company **i** on day **t** over the event window [0,1].

3.2 T-tests

We conduct statistical t-tests for unequal variances, like Loh and Stulz (2018), to determine if the average two-day CAR differs significantly between the treatment period and the control period. We conduct tests on purchase and sales transactions on an aggregate level and for all four insider roles separately. The test statistics are calculated, and p-values are analyzed. The test statistics are laid out by Newbold et al. (2013) as follows, where $\bar{\mathbf{x}}$ and $\bar{\mathbf{y}}$ denote sample means, **s** equals the sample variance and **n** is the sample size:

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

We hypothesize that insider sales and purchases are likely to yield larger CARs during the treatment period **T**, compared to the control period **C**. Hence, we use a one-sided t-test for testing the aggregate sub-samples of purchase and sales transactions. The corresponding null and alternative hypotheses are as follows:

Insider purchase transactions:

$H_0: \overline{CAR_T} - \overline{CAR_C} \leq 0$

$H_1: \overline{CAR_T} - \overline{CAR_C} > 0$

Insider sales transactions

$H_0: \overline{CAR_T} - \overline{CAR_C} \geq 0$

$H_1: \overline{CAR_T} - \overline{CAR_C} < 0$

For testing the sub-samples based on insider roles, where the expected directions of the stock market reaction during the treatment period compared to the control period is less theoretically evident between the specific roles and we instead conduct Welch's t-tests. These are two-sided tests resulting in the following null and alternative hypotheses:

<u>Insider purchase and sales transactions</u>

$$H_0: \overline{CAR_T} - \overline{CAR_C} = 0$$

$$H_1: \overline{CAR_T} - \overline{CAR_C} \neq 0$$

3.3 Panel Regressions

This thesis further adopts the methodology of Loh and Stulz (2018) and conducts panel regression analysis on the stock market reaction resulting from insider transactions. As Loh and Stulz's (2018) methodology is tailored to control for analyst, firm and recommendation characteristics this paper includes control variables from Lakonishok and Lee (2001) and Tavakoli et al. (2012) which are tailored for regressions regarding the informativeness of insider transactions.

Loh and Stulz (2018) conducted their analysis over several industries and included industry fixed effects. As this thesis only includes three industries, biotech, life sciences and pharmaceutical, we control for sub-industry fixed effects, based on SIC codes, as some variation in the CARs might be due to differing characteristics within the sub-industries. The fixed effect is included to control if omitted variables in our dataset vary across the different industries, which could be legislation, news coverage and success in clinical trials from competitors (Stock & Watson, 2019). Appendix A displays Breusch-Pagan tests for our regressions, determining if the Gauss-Markov theorem assumptions are violated due to heteroscedasticity (Stock & Watson, 2019). As seen, we reject the null hypothesis of homoscedasticity for all regressions, on a 1% significance level, except for purchase transactions of *Others*. This leads to us using robust standard errors, i.e., White standard errors, in all regressions to correct for heteroscedasticity. Thus, we control for firm, share and transaction characteristics with the following variables:

Figure 3: Dependent variables

Variable	Type	Definition
COVID19	Treatment	Dummy variable indicating if control period (pre-COVID-19) or treatment period (COVID-19).
Transaction size	Control	Continuous variable controlling for the number of shares in the transaction divided by the total number of shares outstanding. Expressed in ‰.
Within7days	Control	Dummy variable indicating if the transaction was conducted within seven days following the release of a financial report.
Debt to Equity	Control	Company's debt to equity ratio. Equal to total debt divided by total equity.
ROE	Control	Company's return on equity ratio. Equal to net income divided by equity.
BM	Control	Book value of company's equity to market value of equity. Fama and French (2006) book-to-market equity ratio.
PE	Control	Company's price per share as a fraction of earnings per share.
Volatility	Control	The standard deviation of daily stock returns in the prior month (21 trading days).

Note: This table displays the dependent variables used in the panel regressions, which controls for transaction, firm and share characteristics.

The control variables in figure 3 form the following panel OLS regression:

$$CAR = \beta_0 + \beta_1 COVID19 + \beta_2 Transaction\ size + \beta_3 Within7days + \beta_4 Debt\ to\ Equity + \beta_5 ROE + \beta_6 BM + \beta_7 PE + \beta_8 Volatility + \varepsilon$$

The regression shown above is applied on an aggregate level and for all the different insiders' roles and their individual effects on the stock market reaction. Based on this we conduct the following regressions:

Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
All roles	Directors	Officers	Shareholders	Others

3.4 Difference-in-Differences

Deviating from Loh and Stulz (2018), we conduct a difference-in-differences test as a robustness test. We include the test because the causal relationship between insider transactions and stock prices is more ambiguous than an analyst's recommendation and its stock-price impact. We aim to test whether the stock market as a whole reacted differently to insider transactions during COVID-19 or if the healthcare industry differed. Difference-in-differences is a statistical method in which one analyses the effect of a treatment on a treatment group compared with a control group (Angrist & Pischke, 2009). Our thesis compares the two-day CARs following the reporting of an insider transaction in the healthcare industry to S&P 500 companies, which proxies for the overall stock market reaction to filings of insider transactions. We have chosen these companies because they represent a wide variety of industries and sectors. In addition, the 503 constituent companies comprise about 80% of the American Equity, based on market capitalization (S&P Dow Jones, 2022). The treatment is, therefore, the COVID-19 pandemic and the treatment group is the biotech, life sciences and pharmaceutical companies, while the control group is the S&P 500 constituent companies. We removed all companies from S&P 500 that existed in both groups. The method relies on several assumptions, including a parallel trends assumption. In this case, it assumes that the stock-price impact of an insider transaction pre-COVID shows a counterfactual trend, which would have continued if the treatment, i.e., COVID-19, did not occur. Thus, the CARs of the treatment and control group would be parallel during our control and treatment period in the absence of COVID-19. We, however, expect the CARs to differ between the treatment and control period. According to Angrist and Pischke (2009), the parallel trends assumption cannot be fully statistically proven but rather statistically tested, see appendix B, or theoretically motivated. We test the parallel assumption by breaking down the control and treatment period into quarterly time dummies and regress CAR on them, omitting 2019Q4 due to the dummy variable trap, resulting in it serving as a baseline for all the other time dummies. The quarterly dummies are then multiplied with a dummy indicating whether the inside transaction was conducted by a company in our treatment or control group, which forms interaction estimates. Thereafter, the p-values for the pre-treatment estimates are studied to determine if they are insignificant in the pre-treatment period compared to the baseline case of 2019Q4, thus, proving the parallel trends assumption. Control variables and fixed effects are not included in the tests as Angrist and Pischke (2009) argued that the parallel trends assumption should hold for raw data. For the robustness test, we conduct two difference-in-differences for purchases and sales individually by creating one dummy variable for COVID-19 and another for our treatment group, the healthcare companies. These two dummy variables are multiplied to form the difference-in-differences variable, commonly known as the interaction variable. We then run the regression on both dummy variables and the difference-in-differences variable, this time including the control variables in figure 3 and controlling for industry-specific effects using SIC codes. The fundamental objective of the test is to determine the treatment effect, measured by the interaction effect in the following regression:

$$CAR = \beta_0 + \beta_1 TIME\ PERIOD + \ \beta_2 DATASET + \ \beta_3 DiD + \sum_{i}^{k} \gamma_i x_{it} + \varepsilon$$

Where:

TIME PERIOD = 0 if control period (pre-COVID), 1 if treatment period (COVID)

DATASET = 0 if S&P 500, 1 if healthcare

$\mathrm{DiD} = \mathrm{TIME\ PERIOD} \times \mathrm{DATASET}$

x_{it} = control variables in figure 3

3.6 Sample and Delimitations

This study focuses on insider transactions conducted in public U.S. companies within the biotech, life sciences and pharmaceutical industries. The categorization was done based on SIC codes from CapitalIQ and is denoted as the healthcare industry. A company list was not extracted from CapitalIQ to avoid a survivorship bias, as CapitalIQ initially only listed active firms. The data consists of companies appearing on the NYSE, AMEX and Nasdaq stock markets, which reported at least one insider trade during the period 2018-01-01 to 2021-12-31. All data used in the thesis was retrieved from CRSP, Compustat and Thomson/Refinitiv via the WRDS database during the autumn of 2022.

Insider transaction data was gathered from Refinitiv under the section *Insiders Data*, which contains all insider transactions filed to the SEC. This consists of insider transactions subject to disclosure by 16(a) of the Securities and Exchange Act of 1934 (SEA), which covers transactions of common stocks. The data retrieved are from forms 3, 4 and 5. Transactions including less than 100 shares were excluded, allowing us to focus on the more meaningful events.[3] Additionally, like Lakonishok and Lee (2001), we dropped trades in which the number of shares exceeded 20% of the number of shares outstanding.

[3] The data do not include transactions from Form 144, which is filed when an insider intends to sell restricted, or unregistered shares.

The insiders were classified into four groups: *Directors* including roles as the chairman of the board, director, president, vice president, *Officers* including all executive officers such as CEO, CFO and COO, *Shareholders* are individuals owning more than 10% of the shares without having any of the previously mentioned roles. *Others* consist of individuals subject to reporting to the SEC but are not directors, managers, nor large shareholders typically, company lawyers, relatives and other affiliative people of the company. We extracted insider purchase and sales transactions defined as open market or private sales, respectively, and divided them into sub-samples based on the transaction code reported to the SEC, indicating the type of transaction.[4]

Stock market data from the NYSE, AMEX and Nasdaq markets, including opening and closing prices and index returns, were gathered from CRSP. Companies with a share price of less than $1 were excluded to avoid noise potentially generated by penny stocks, similar to Lakonishok and Lee (2001). Financial data and ratios were retrieved from the CRSP – Compustat merged database, with quarterly financial figures allowing for the most recent data to be used.

The data consists of 101,293 transactions, of which 45,573 and 55,720 are conducted in the healthcare and S&P 500 companies, respectively. Among the healthcare companies, there were 38,865 purchases and 6,708 sales during the entire time period of the study (e.g., 2018-01-01 to 2021-12-31).

[4] Data with transaction code P and S were retrieved as it represents purchase and sales transactions respectively.

Figure 4: Sample selection

Sample		Sample Attrition	Insider Transactions
Initial sample from Thomson/Refinitiv During 2018Q1-2021Q4	**Total**		**61,047**
	Purchases		**13,414**
	Sales		**47,633**
Removal of transactions missing price of transaction and number of shares.	Total	-29	61,018
	Purchases	*-28*	*13,386*
	Sales	*-1*	*47,632*
Excluded transactions with less than 100 shares.	Total	-3,402	57,616
	Purchases	*-1,178*	*12,208*
	Sales	*-2,224*	*45,408*
Excluded companies with a daily share price of less than $1	Total	-1,202	56,414
	Purchases	*-876*	*11,341*
	Sales	*-335*	*45,073*
Excluded transactions with the number of shares larger than 20% of the total number of shares outstanding	Total	-20	56,934
	Purchases	*-15*	*11,341*
	Sales	*-5*	*45,073*
Removal of transactions lacking financial data	Total	-10,821	45,573
	Purchases	*-4,618*	*6,708*
	Sales	*-6,203*	*38,865*
Insider transactions in final sample	**Total**		**45,573**
	Purchases		**6,708**
	Sales		**38,865**

Note: This table reports the sample selection procedure of the insider transactions in healthcare companies.

4. Results

4.1 Descriptive Statistics

This section presents the descriptive statistics for the two-day cumulative abnormal return based on transaction type and job role, as seen in figure 5 and 6. Additionally, it displays descriptive statistics of our independent variables in figure 7 and 8. All descriptive statistics regard insider transactions within the biotech, life sciences and pharmaceutical industries.

Descriptive statistics of the two-day CARs for purchase and sales transactions and by insider role two-day CARs of purchase and sales transactions are displayed, respectively, in figure 5 and 6. Surprisingly, the number of sales is much larger than the number of purchases with 6,708 sales transactions, compared to 38,865 purchase transactions. This might be explained by open market purchases being less common than sales of shares as the insiders might obtain shares in other ways; equity swaps, the exercise of an option, or awards and other acquisitions pursuant according to Rule 16b-3(d) in the SEA, which covers transactions regarding insiders' participation in employee benefit plans (SEC, 2021). The increase in insider transactions during COVID-19, displayed in figure 1, is mainly explained by the increase in sales from 15,294 during the control period to 23,571 during the treatment period. *Officers* and *Directors* conducted the most purchase transactions, with a slight difference of 323 transactions between them. Among sales transactions *Officers* account for 24,387 out of total 38,865 transactions. Following our expectations, the mean of purchase transactions over all insider roles during both periods is 1.60%, while the mean of sales transactions is -0.36%. All roles, over the treatment and control period, have high volatility in returns with purchase transactions having a standard deviation of around 7.00% and above, while sales have a standard deviation of around 5.00%. Focusing on the distribution of the different roles, surprisingly, shows that the 25th percentile is similar for both transaction types laying around 2.50% for both purchases and sales. However, the 75th percentile is larger among purchases equal to 4.59%, compared to 1.90% for sales. Looking at the median among all roles *Shareholders* has CAR with 1.03% and -0.50% for purchase and sales, correspondingly.

Figure 5: Descriptive statistics of purchase transactions

	N	***Mean***	***Std. Dev***	***Min***	***25th***	***Median***	***75th***	***Max***
Role								
Total	**6,708**	**1.60%**	**9.69%**	**-34.71%**	**-2.51%**	**0.60%**	**4.59%**	**151.52%**
Control	3,349	0.38%	6.17%	-25.28%	-2.71%	0.13%	3.64%	44.66%
Treatment	3,359	2.81%	12.12%	-34.71%	-1.93%	1.10%	6.10%	151.52%
Directors	**2,351**	**2.63%**	**11.76%**	**-34.71%**	**-2.05%**	**0.69%**	**5.09%**	**151.52%**
Control	945	0.58%	6.84%	-23.09%	-2.71%	0.23%	3.19%	44.66%
Treatment	1,406	4,01%	13,97%	-34,71%	-1,33%	0,86%	6,81%	151,52%
Officers	**2,674**	**0.78%**	**9.07%**	**-25.43%**	**-3.15%**	**0.14%**	**3.77%**	**151.52%**
Control	1,649	-0.13%	5.77%	-25.28%	-3.15%	-0.30%	3.23%	44.66%
Treatment	1,025	2.24%	12.56%	-25.43%	-3.19%	1.18%	5.04%	151.52%
Shareholders	**1,585**	**1.47%**	**6.90%**	**-24.48%**	**-1.89%**	**1.03%**	**5.06%**	**31.34%**
Control	727	1.25%	5.99%	-21.66%	-1.83%	0.99%	4.36%	28.02%
Treatment	858	1.66%	7.59%	-24.48%	-1.94%	1.29%	5.73%	31.34%
Others	**98**	**1.10%**	**7.53%**	**-12.53%**	**-3.44%**	**0.27%**	**6.30%**	**20.59%**
Control	28	1.64%	6.77%	-10.24%	-3.11%	0.65%	7.51%	15.63%
Treatment	70	0.88%	7.85%	-12.53%	-3.45%	0.23%	5.98%	20.59%

Note: This table displays descriptive statistics of the independent variable two-day (CAR) for purchase transactions, split by insider roles during the entire period, the control and treatment period.

Figure 6: Descriptive statistics of sales transactions

	N	*Mean*	*Std. Dev*	*Min*	*25th*	*Median*	*75th*	*Max*
Role								
Total	**38,865**	**-0.36%**	**5.19%**	**-81.25%**	**-2.58%**	**-0.29%**	**1.98%**	**82.19%**
Control	15,294	-0.23%	3.90%	-27.08%	-1.91%	-0.20%	1.57%	39.22%
Treatment	23,571	-0.44%	5.88%	-81.25%	-3.17%	-0.37%	2.33%	82.19%
Directors	**9,824**	**-0.31%**	**5.77%**	**-81.25%**	**-2.76%**	**-0.25%**	**2.07%**	**82.19%**
Control	3,542	-0.26%	3.77%	-17.70%	-2.12%	-0.23%	1.64%	28.62%
Treatment	6,282	-0.33%	6.64%	-81.25%	-3.31%	-0.27%	2.42%	82.19%
Officers	**24,387**	**-0.32%**	**4.77%**	**-37.33%**	**-2.47%**	**-0.27%**	**1.96%**	**80.99%**
Control	9,987	-0.16%	3.67%	-22.83%	-1.69%	-0.20%	1.54%	39.22%
Treatment	14,400	-0.43%	5.40%	-37.33%	-3.10%	-0.33%	2.34%	80.99%
Shareholders	**3,022**	**-0.92%**	**6.65%**	**-27.08%**	**-3.53%**	**-0.50%**	**1.81%**	**67.72%**
Control	1,123	-1.07%	5.64%	-27.08%	-3.43%	-0.59%	1.52%	21.78%
Treatment	1,899	-0.83%	7.19%	-20.21%	-3.71%	-0.50%	1.99%	67.72%
Others	**1,632**	**-0.26%**	**4.41%**	**-24.18%**	**-2.38%**	**-0.27%**	**1.90%**	**38.64%**
Control	642	0.31%	4.10%	-18.76%	-1.43%	0.07%	1.87%	38.64%
Treatment	990	-0.63%	4.56%	-24.18%	-3.02%	-0.68%	1.92%	21.40%

Note: This table displays descriptive statistics of the independent variable two-day (CAR) for sales transactions, split by insider roles during the entire period, the control and treatment period.

The descriptive statistics of our independent variables, as seen in figure 7 and 8, generally align with our expectations. As expected, the average transaction size of an insider transaction is larger for purchase transactions averaging 2.32‰, compared to sales transactions averaging 0.44‰. The mean *ROE* in absolute numbers is larger for purchases at 101.44%, while 35.40% for sales, with both being negative. The mean *Debt to Equity* is smaller for purchase transactions equaling -0.34, while it is 0.97 for sales transactions. For both transaction types most transactions are conducted within seven days of a financial report release. Purchase transactions conducted before and during COVID-19 were equally distributed between the two periods. In contrast, 60.65% of insider sales occurred during COVID-19, and 39.35% before.

Figure 7: Descriptive statistics of independent variables for purchase transactions

	N	*Mean*	*Std. Dev*	*Min*	*25th*	*Median*	*75th*	*Max*
Tran size (‰)	6,708	2.38	10.91	0.00	0.01	0.08	0.45	184.84
Debt to equity	6,708	-0.34	45.97	-1,313.10	0.23	0.41	1.00	174.16
ROE (%)	6,708	-101.44	333.16	-8,079.76	-97.21	-34.67	-9.83	354.13
BM	6,708	0.50	0.48	-1.09	0.14	0.35	0.80	5.51
PE	6,708	-0.82	145.09	-4,057.72	-9.23	-4.79	-1.77	8,897.33
Volatility	6,708	0.04	0.03	0.00	0.02	0.03	0.05	0.71
COVID19	**6,708**	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Yes	3,359	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
No	3,349	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Within7days	**6,708**	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Yes	5,179	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
No	1,529	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

Note: This table reports the descriptive statistics of the independent variables. The data includes 6,708 insider transactions. N/A indicates that no value is derived.

Figure 8: Descriptive statistics of independent variables for sales transactions

	N	*Mean*	*Std. Dev*	*Min*	*25th*	*Median*	*75th*	*Max*
Tran size (‰)	38,865	0.44	3.45	0.00	0.01	0.04	0.16	189.58
Debt to equity	38,865	0.97	10.36	-401.45	0.25	0.49	1.38	174.16
ROE (%)	38,865	-35.40	185.75	-8,079.76	-49.45	-18.82	13.60	1,545.35
BM	38,865	0.17	0.17	-6.26	0.09	0.15	0.22	3.20
PE	38,865	2.41	335.82	-20,662.96	-16.38	-5.21	28.28	11,123.52
Volatility	38,865	0.03	0.03	0.00	0.01	0.02	0.03	0.60
COVID19	**38,865**	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Yes	23,571	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
No	15,294	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Within7days	**38,865**	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Yes	26,653	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
No	12,212	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*

Note: This table reports the descriptive statistics of the independent variables. The data includes 38,865 insider transactions. N/A indicates that no value is derived.

4.2 T-tests

Figure 9 displays our t-tests with change in two-day CAR during COVID-19 compared to the control period, without controlling for firm, share or transaction characteristics. On an aggregate level the one-sided t-test displays that the average two-day CAR for purchases increased by 2.42% while sales decreased by 0.21%, both significant at the 1% significance level. When studying results based on job roles, the two-sided t-tests show that *Officers* was the only group to experience a significant change in two-day CAR during COVID-19 for both purchase and sales transactions. For purchases and sales *Officers*' two-day CAR increased by 2.46% and decreased by 0.24% respectively, both larger than the average change of each transaction type on an aggregate level. *Directors*' market reaction only significantly changed for purchase transactions with the average two-day CAR increasing by 3.44% at the 1% significance level. *Others* only display a significant change for sales transactions, at the 1% significance level with a decrease of 0.87% in two-day CAR from the reporting day. The results display that all significant changes, at the 1% significance level on an aggregate level and for each job role individually, were larger in terms of magnitude for purchase transactions. The significant changes, at the 1% significance level, for purchase transactions were all positive and negative for sales.

Figure 9: T-test Results

	Dependent variable: Two-Day CAR (%)	
Role	Purchases	Sales
All	2.42*** (10.32)	-0.21*** (4.27)
Directors	3.44*** (7.92)	-0.07 (0.71)
Officers	2.46*** (5.75)	-0.24*** (4.12)
Shareholders	0.41 (1.19)	0.24 (1.03)
Others	-1.12 (0.70)	-0.87*** (4.18)

Note: This table reports the difference in average two-day CAR (in percent) between the control period and the treatment period for the different transaction types and different job roles. CAR is calculated over the [0,1] event window, with the event date defined as reporting day. In total, the data consists of 45,573 insider transactions. t-statistics (in parenthesis and in absolute values). *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

4.3 Panel Regressions

Figure 10 and 11 display the regression results for purchase and sales transactions, with two-day CAR as the dependent variable, controlling for firm, share and transaction characteristics, in addition to industry fixed effects. The results align with our t-tests, displaying positive significant changes in market reactions, for purchases, on an aggregate level as well as for *Directors* and *Officers*, as seen in figure 10.

Figure 10: Regression results for purchase transactions

	Dependent variable: Two-Day CAR				
Variable	All	Directors	Officers	Shareholders	Others
COVID19TRUE	2.70*** (0.26)	3.93*** (0.46)	2.00*** (0.35)	0.38 (0.38)	0.89 (1.59)
Transaction Size	-11.20 (11.15)	-50.15** (25.08)	109.17** (48.02)	5.24 (11.79)	151.37*** (46.79)
Within7days	0.48 (0.33)	1.23** (0.61)	0.17 (0.36)	-0.86* (0.52)	-5.64*** (2.11)
Debt to Equity	-0.01*** (0.00)	-0.01*** (0.00)	0.01*** (0.00)	0.02*** (0.01)	0.18 (0.20)
ROE	0.06** (0.02)	0.16*** (0.04)	0.04 (0.07)	-0.06 (0.06)	-0.43 (0.48)
BM	-0.43* (0.24)	0.80 (0.52)	-0.26 (0.35)	0.49 (0.50)	1.36 (1.58)
PE	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)	0.01*** (0.00)	0.00 (0.00)
Volatility	66.08*** (10.19)	141.93*** (16.76)	-16.26*** (-6.79)	-24.80** (11.36)	0.95 (34.37)
Industry F.E	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.20	0.08	0.02	0.13
Adj. R^2	0.07	0.19	0.07	0.01	-0.04
Observations	6,708	2,351	2,674	1,585	98

Note: This table presents the effect of purchase transactions on two-day CAR (in percent) over the [0,1] event window with reporting day defined as the event date, on an aggregate level and by each job role. The data includes 6,708 purchase transactions. Robust standard errors (White) in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Overall, as seen in figure 10, the results demonstrate a positive correlation between purchase transactions and cumulative abnormal returns. The regression results differ somewhat from the t-tests' cumulative abnormal returns, due to the linear regression controlling for other variables, perhaps isolating the effect of insider trading.

Figure 11: Regression results for sales transactions

	Dependent variable: Two-Day CAR				
Variable	All	Directors	Officers	Shareholders	Others
COVID19TRUE	-0.26*** (0.05)	-0.30*** (0.11)	-0.29*** (0.06)	-0.16 (0.26)	-0.82*** (0.23)
Transaction Size	0.45 (18.43)	52.94* (26.98)	-1.88 (33.73)	-1.83 (25.81)	-20.08 (13.51)
Within7days	-0.32*** (0.06)	-0.19 (0.13)	-0.48*** (0.07)	0.62** (0.25)	-0.84*** (0.25)
Debt to Equity	0.00 (0.00)	-0.01 (0.01)	0.00 (0.00)	0.08*** (0.02)	-0.02** (0.01)
ROE	-0.01 (0.03)	0.06 (0.05)	-0.05 (0.04)	-0.62** (0.32)	0.09 (0.06)
BM	-0.74*** (0.19)	-1.34*** (0.40)	-0.71** (0.34)	-0.22 (0.34)	-0.74 (1.62)
PE	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00*** (0.00)	0.00 (0.00)
Volatility	17.36*** (5.90)	52.57*** (12.43)	6.38 (4.40)	-29.24*** (5.22)	13.64 (15.88)
Industry F.E	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.07	0.00	0.03	0.02
Adj. R^2	0.01	0.07	0.00	0.02	0.01
Observations	38,865	9,824	24,387	3,022	1,632

Note: This table presents the effect of sales transactions on two-day CAR (in percent) over the [0,1] event window with reporting day defined as the event date, on an aggregate level and by each job role. The data includes 38,865 purchase transactions. Robust standard errors (White) in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

The linear regression results for sales transactions, displayed in figure 11, are in line with the t-tests' results on both an aggregate level as well as for *Directors*, *Officers* and *Others*. On an aggregate level, opposite to purchase transactions, the results display a negative correlation between sales transactions and two-day CAR following the reporting day. Contrary to our t-tests, *Directors* also yielded a change in market reaction during COVID-19, with -0.30% at the 1% significance level. All roles that yielded a significant change in market reaction for sales, at the 1% significance level also show a negative correlation with cumulative abnormal returns.

The models' adjusted R^2 is relatively low, thus, explaining a low amount of the variation in the data for both the sample containing purchase and sales transactions. This is, however, not surprising, as our model ought to explain abnormal returns consisting of only eight independent variables. As seen in appendix C, we test for multicollinearity in our model and its independent variables by calculating the variance inflation values (VIF). With no VIF value exceeding the common threshold of 10, we deem multicollinearity not to be a problem in our regressions.

4.4 Difference-in-Differences

The difference-in-difference tests, as seen in figure 12, show that there is a significant difference in the dummy variable *DATASET*, implying that there is a significant negative difference in CARs between the healthcare industry and the overall stock market. It shows that the healthcare companies' sales transactions experienced 0.18% less in two-day CARs and purchase transactions experienced 1.82% less in two-day CARs compared to the S&P 500 companies during the entire period. *DATASET* does not take the treatment and control period into consideration separately. The dummy variable *TIME PERIOD* indicates if there is a difference in two-day CARs between the control and treatment period, without differing between the control group and treatment group. For purchase transactions there is no significant effect. However, there is a -0.21 % difference between the two time periods for sales transactions, indicating that abnormal returns for the following two trading days are negatively larger in magnitude. The test combines the dummy variables *DATASET* and *TIME PERIOD* to test if the product of the two variables is significant. The results align with our expectations; there is a positive treatment effect in purchase transactions of 2.22% at a 1% significance level, i.e., the conditional probability of a Type 1 error (false positive), meaning rejecting the null hypothesis when it is in fact true is less than 1%. This indicates that CARs of purchase transactions are larger in the healthcare industry than in the overall stock market during the treatment period. Surprisingly the OLS estimate for the dummy *DATASET* for purchases is negative, showing that the healthcare industry experienced smaller market reactions compared to the overall stock market. The results of sales transactions further confirmed our beliefs, as the sign of the interaction term is negative as expected but shows no significance at a 10% significance level.

This indicates that there is no significant change between the overall stock market and the healthcare industry between the control and treatment period.

Figure 12: Difference-in-differences result

	Dependent variable: Two-Day CAR	
Variable	Purchases	Sales
DATASET	-1.82*** (0.54)	-0.18** (0.08)
TIME PERIOD	0.49 (0.32)	-0.21*** (0.02)
DiD	2.22*** (0.43)	-0.03 (0.06)
Industry F.E	Yes	Yes
R^2	0.08	0.01
Adj. R^2	0.06	0.01
Observations	7,802	93,493

Note: This table reports the regression results (in percent) for the difference-in-differences regressions with two-day CAR as the dependent variable. The data covers in total 101,293 insider transactions. 45,573 and 55,720 insider transactions are conducted by the healthcare companies and S&P companies, respectively. The control period includes 37,590 transactions, and the treatment period includes 63,703 transactions. Robust standard errors (White) in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

5. Discussion of Results

In this section we will analyze our results, connect them to our hypotheses and suggest possible implications. The first discussion will cover insider transactions' impact on market reactions on an aggregate level, followed by a discussion about each transaction type independently. Lastly, we provide a discussion of the impact of each insider role separately on market reaction. A summary of our results compared to the previous empirics can be found in appendix D.

5.1 Healthcare

In our study, we found that insiders’ filings within the healthcare industry yielded significant changes in market reaction for both sales and purchases during COVID-19, which supports hypothesis 1. This aligns with our benchmark papers, Loh and Stulz (2018) and Lakonishook and Lee (2001). However, as mentioned in the literature review, we examine insider transactions and not analysts’ recommendations, which Loh and Stulz (2018) do. Previous studies such as Fidrmuc et al. (2006) and Friederich (2002) also attained the same results. Contributive to Kacperczyk et al. (2017) our study shows that insiders within the healthcare industry generate greater market reactions during the uncertainty of COVID-19. As there are many plausible explanations for this, one reason could be that market investors rely more on provided information during times of uncertainty (Loh & Stulz, 2018).

COVID-19 attracted much attention to the healthcare industry, which should on the other end diminish insiders' informational advantage and value to the market. Loh and Stulz (2018) and De Bondt and Thaler (1986) emphasized the influence of the overreaction of outside investors. Following their findings, it seems reasonable that the market overreacted to the insider trades because of the uncertainty, which yielded larger market abnormal returns than before the pandemic. However, our thesis only partly supports the findings of Adooby and Lev (2002), in addition with Coff and Lee (2003), who showed higher abnormal returns in heavy R&D industries compared to low R&D-intensive industries. Our results from the difference-in-differences tests only display a significant difference in two-day CARs of purchase transactions during the treatment period between the healthcare industry and the overall stock market. This is partly inconsistent with hypothesis 1 since it indicates that only purchase transactions experienced changes in market reactions during COVID-19. Furthermore, our results contradict Chowdhury et al. (1993) since we find a correlation between the macroeconomic event of COVID-19 and abnormal returns arising from insider transactions.

5.2 Purchase and Sales

Throughout our results, purchases and sales displayed a positive and negative correlation with two-day CAR, respectively. This supports our second hypothesis that purchases should be seen as good news, and sales as bad news for outside investors. Additionally, it aligns with Loh and Stulz (2018), who concluded negative abnormal returns following downgrades in analysts' recommendations and positive abnormal returns following upgrades. The result of our study shows a greater change in two-day cumulative abnormal returns for purchases than for sales, which is in line with previous research, although earlier studies has been somewhat inconclusive on the matter. Our results, support our third hypothesis theorizing that purchases should be perceived as more informative compared to sales; hence, generating larger market reactions. This does not align with Schmalz and Zhuk (2018), who observed greater sensitivity of stock prices to bad news, as compared to good news during times of uncertainty. Our results show that on an aggregate level purchase transactions and sales transactions, on average, experienced an increase of 2.42% and a decrease of 0.21% in two-day CAR during COVID-19 respectively. Contrary to the findings of our study, Lakonishok and Lee (2001) found higher market reactions for sales. In addition, Chang and Suk (1998) also showed higher market reactions for sales than for purchases. Further, our thesis partly contradicts Veronesi (1999), as we find higher reactions to good news, compared to bad news, while Veronesi's results showed that investors overreact to bad news, compared to good news during uncertain times.

However, Tavakoli et al. (2010) and Jeng et al. (2003) support our findings of higher market reaction for purchases. This is elevated by our findings that purchase transactions show a significant uprise in stock market reaction during COVID-19. Sales, on the other hand, did not show a statistically significant change. Further, Tavakoli et al. (2010) and Lakonishok and Lee (2001) and Jeng et al. (2003) found that one plausible explanation for purchases to have a higher effect is because sales can disregard the future performance of the company and be pursued because of liquidity reasons or other personal interests. In fact, the compensation system is different in the U.S. compared to other countries, which could make our results specific for the geographical market in our study. For instance, in the U.S. a common salary compensation tool is Restricted stock unit (RSU). It allows one to sell shares in the open market within a specific time frame in order to liquidate the RSU issued by the company (Lee, 2021). Thus, this could lead to insider sales having less or no signaling value for the market, which is to some extent displayed in our results. This finding is in line with what we expected in hypothesis 3.

5.3 Insider Roles

Regarding the different insider sub-groups, more influential insiders seem to be associated with higher market reactions. Our study's results show that the change in market reaction in the expected direction, mentioned in hypothesis 3, was significant for *Officers* for both transaction types while *Directors* only showed a significant change for purchases.[5] This partly supports hypothesis 4, stating that the correlation increases between reporting of the trade and the market reaction the more influential and operationally responsible a role is. Our findings, that more influential roles display higher abnormal returns, are in line with previous research done by Seyhun (1986), Wang et al. (2012) and Degryse (2009). In addition, Tavakoli et al. (2010) support our results since their study found predictive power for directors across all firms, yet only found predictive power for officers in small firms

[5] As theorized in hypothesis 3: sales are expected to yield negative cumulative abnormal returns, while purchases are expected to yield negative cumulative abnormal returns.

One plausible explanation for the higher market reaction to *Directors'* purchases, compared to *Officers* could be explained by Tavakoli et al. (2010). In our study, firm size is not included and could therefore serve as an explanation for *Officers* having lower market reactions than directors. Further, they also found that the trading actions of directors and officers influence other insiders, yet the former to a larger extent. The influence of directors' trading on the stock market is possibly amplified by its impact on other insiders' trading, which in turn serve as separate signals to outside investors. This possibly explains the larger market reactions we find for purchases of *Directors*, compared to *Officers*. Our findings, contradictory to Tavakoli et al. (2010), show no significant results among directors' sales; but the cause thereof remains unanswered. One possible explanation for sales having lower signaling value than purchases is, according to Lakonishok and Lee (2001), Jeng et al. (2003) and Kallunki et al. (2009), that insiders sell their private stocks because of liquidity reasons, tax considerations, behavioral bias or other personal reasons. Based on this, hypothesis 4 cannot be fully supported. The difference in market reactions is more evident when studying *Directors* and *Officers* together, compared to *Shareholders* and *Others* together. This is most likely explained by the fact that the two groups have significantly different access to private information (Seyhun, 1986). However, when studying all roles separately, the results provide weaker support for our fourth hypothesis. Yet, our study mostly aligns with the hierarchical information hypothesis in Seyhun (1986).

Summary of discussion

A summary of our findings of cumulative abnormal returns, compared to previous literature, can be found in appendix D. Overall, our results show enough evidence to confirm two out of the four hypotheses, the other two hypotheses are partly confirmed.

Figure 13: Results' indication for hypotheses

Hypothesis 1:	*Insider transactions yield greater market reactions during COVID-19.*	Partly
Hypothesis 2:	*Purchase transactions yield positive abnormal returns, and sales transactions yield negative abnormal returns, during COVID-19.*	Supported
Hypothesis 3:	*Insider purchase transactions will have a higher signaling effect than sales to outside investors, during COVID-19.*	Supported
Hypothesis 4:	*More operationally influential roles result in larger market reactions, during COVID-19.*	Partly

6. Concluding Remarks

6.1 Data and Method Limitations

The data was collected from CRSP, Thomson/Refinitiv and Compustat, all used by accounting and finance professionals in research, implying that the source is reliable. However, one limitation of the data is that the reporting time and stock prices were retrieved on a daily basis and not on an hourly basis. Based on this, we assumed that each filing was considered public information at the start of each trading day. The filing, in reality, possibly occurs outside of market hours. This limits the reliability of the results somewhat, as the cumulative abnormal returns calculations are not as true to reality as possible. We cannot assume or reject whether this retrieving error occurs randomly or systematically, thus decreasing the reliability of our results.

We adapted the methodology of Loh and Stulz (2018) with inspiration from Lakonishok and Lee (2001). Our calculation of abnormal returns, following Seyhun (1998), by extracting the

NYSE/AMEX and Nasdaq equally weighted index from the company's daily return could imply some limitations for our methods. This does not consider idiosyncratic risk as a CAPM, following, for instance, a Fama French three-factor or five-factor model would (Fama & French, 1993). Hence, the abnormal return calculated could imply some inaccuracies in our results as it is our dependent variable and thus, the measure of the stock market return.

Moreover, in our difference-in-differences test we used the companies constituting the S&P 500 index as a proxy for the overall stock market. This assumption does not perfectly represent the entire market. During uncertain times smaller companies might be affected differently compared to the largest 500 companies, resulting in a skewed perspective of the overall stock market's reaction to insider transactions. However, conducting a study based on every company listed would be infeasible for our technical resources. Furthermore, we theoretically assume parallel trends in the difference-in-differences test during the control period between healthcare and S&P 500. We also decided to statistically test this assumption, in appendix B, by regressing CAR on the interaction variables with quarterly leads and lags to test for insignificance. However, the test does not imply a perfect result. For sales, 4 out of 8 of the leads are indeed significant at a 1% significance level and for purchase transactions two out of 8 leads were significant when compared to the left-out baseline interaction effect of 2019Q4. Significant results violate the parallel trends assumptions to some extent, as some quarters show deviation from the trend. Thus, the creation of a counterfactual trend involves statistical limitations.

Overall, the method relies upon the assumption that the control period of 2018-01-01 to 2019-12-31 serves as a time of certainty and low financial risks. This is not the case, as events occurring during this time period, such as the 2018 U.S. presidential election, the U.S. leaving the Iran Nuclear Deal, the Trade War with China and the escalation of the political situation in Hong Kong presumably also caused uncertainty. Thus, assuming the control period is the opposite of the uncertainty experienced during COVID-19 implies limitations to our results. However, we argue that the limitations and changes mentioned above are, to different extents, minor and would not change the overall implications of our method and results.

6.2 Conclusion

To conclude, this study investigates whether the uncertain climate of COVID-19 affected the perceived informativeness of insider transactions in the U.S. biotechnological, life sciences and pharmaceutical industries. The perceived informativeness is measured by a market reaction model, which captures the cumulative abnormal returns for the following two trading days from when the transaction was reported to the SEC.

The results of the study show that during COVID-19; 1) insider purchases yielded positive abnormal market returns, and sales yielded negative abnormal market returns, and 2) insider purchases were perceived as more informative compared to sales for market investors. Since the previous literature is inconclusive on the matter, our second finding is somewhat contrary. Overall, we conclude that market investors rely and trade more on insider purchases in healthcare during the uncertainty of the SARS-CoV-2 pandemic.

Given that our results are valid and general, they have practical implications. Contributing to the research about stock markets in crises, market investors can develop investment strategies during these times of uncertainty and predict the market's reaction. However, our findings are too insufficient to build a complete investment strategy and could merely serve as a small piece of the puzzle.

6.3 Future Research

For future studies, it would be relevant to determine how abnormal returns arise following insider trades. For instance, whether the market itself is inefficient, if insiders indeed take advantage of private information, or if signals weigh heavier. All three explanations can serve as reasons why the stock market reactions are greater during times of uncertainty. This study was limited to healthcare companies during COVID-19; an industry experiencing heavy media coverage and attention from the general public. Therefore, examining the market reaction following insider transactions in other industries experiencing similar attention during different crises would be interesting. For instance, the travel and leisure industry during COVID-19, the financial industry during the financial crisis of 2008 and the energy industry after Russia invading Ukraine. Likewise, it would be interesting to study the healthcare industry within the subject of insider transactions during other critical events such as, patent applications, clinical trials, and FDA approvals. Our study is limited to the U.S. exchange markets, and it would be interesting to expand the research to 1) different countries, due to varying regulations and 2) a global scope of the healthcare industry, as many companies operate on an international level. This would add more evidence to the research and deepen the understanding of insider trading.

Finally, our study excludes the regulation aspect of insider trading as we only observe market reactions following the reporting of a trade, as opposed to the actual transaction day and subsequent returns earned by the insiders. If one were to consider both perspectives, one could analyze whether outsiders are put at a disadvantage compared to insiders, and if the regulations should be amended. Lastly, our treatment period is defined using the Oxford COVID-19 Government Response index. Utilizing other uncertainty indexes, such as CBOE VIX for market volatility could possibly isolate the effect of uncertainty. This could also be done by considering several factors, e.g., inflation, unemployment and real personal consumption.

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8. Appendix

Appendix A: Breusch-Pagan test

Transaction type	Regressions				
	All	Directors	Officers	Shareholders	Others
Purchases	9,179***	2,992***	3,987***	3,381***	321***
Sales	19,795****	2,709****	26,870***	526***	16

Note: This table reports the results for the Breusch-Pagan test, testing for heterscedasticity. Significant results indicate that the null hypothesis of homoscedasticity is rejected. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Appendix B: Parallel assumption regression results

Variable	Dependent variable: Two-Day CAR	
	Purchases	Sales
Constant	0.11% (0.08%)	-0.02% (1.70%)
2018Q1:DATASET	-2.75% (0.16%)	0.42%** (2.13%)
2018Q2:DATASET	-2.34% (0.17%)	0.50%** (2.08%)
2018Q3:DATASET	-4.11%* (0.17%)	0.13% (2.20%)
2018Q4:DATASET	-4.16% (0.18%)	-0.40%** (1.98%)
2019Q1:DATASET	-1.11% (0.17%)	0.35%** (2.11%)
2019Q2:DATASET	-4.32% (0.18%)	0.12% (2.67%)
2019Q3:DATASET	-5.85%*** (0.17%)	-0.17% (2.12%)
R^2	0.02	0.02
Adj. R^2	0.02	0.02
Observations	7,802	93,493

Note: This table reports the regression results (in percent) for the parallel assumption regression with two-day CAR as the dependent variable. The data covers in total 101,293 insider transactions. 45,573 and 55,720 insider transactions are conducted by the healthcare companies and S&P companies, respectively. Robust standard errors (White) in parenthesis. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Appendix C: Pearson correlations & VIF Values

Panel A: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) COVID19	1.00							
(2) Transaction size	0.02***	1.00						
(3) Within7days	-0.06***	-0.02***	1.00					
(4) Debt to Equity	-0.00	-0.03***	0.00	1.00				
(5) ROE	-0.00	-0.05***	0.03***	0.04***	1.00			
(6) BM	-0.12***	-0.00	-0.02***	0.02***	0.12***	1.00		
(7) PE	-0.03***	0.00	0.01**	0.00	0.01**	-0.01	1.00	
(8) Volatility	0.07***	0.07***	-0.01***	-0.02***	-0.09***	0.06***	-0.01	1.00

Panel B: Variance Inflation Factors (VIF)

Variables	Purchases	Sales
(1) COVID19	1.039	1.021
(2) Transaction size	1.020	1.005
(3) Within7days	1.005	1.006
(4) Debt to Equity	1.007	1.005
(5) ROE	1.080	1.030
(6) BM	1.125	1.023
(7) PE	1.002	1.001
(8) Volatility	1.014	1.021

Note: This table reports the results of the multicollinearity tests. Panel A reports the Pearson Product Moment Correlation, conducted as a two-tailed test. Panel B reports the variance inflation factors (VIF). *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Appendix D: Evidence of abnormal returns after insider transactions

Study	Sample period	Country	Event Date	Event window	Purchases CAR (%)	Sales CAR(%)
Betzer and Theissen (2009)	2002-2004	Germany	TD	(0;19)	5.79	-5.20
Fidrmuc et al. (2006), all-trades sample	1991-1998	UK	RD	(0;1) (0;4)	1.16 1.65	-0.26 -0.49
Fidrmuc et al. (2006), large-trades sample	1991-1998	UK	RD	(0;1) (0;4)	3.12 4.62	-0.37 -0.53
Bajo and Petracci (2006)	1998-2002	Italy	TD	(0;9)	3.18	-3.67
Jeng et Al. (2003)	1975-1996	U.S.	TD	(0;5) (5;21)	2.84 1.52	0.87 -0.04
Friederich et al. (2002)	1986-1994	UK	TD	(0;1)	0.42	-0.17
Lakonishok and Lee (2001)	1975-1995	U.S.	RD	(0;4)	0.13	-0.23
Chang and Suk (1998)	1988-1990	U.S.	RD	(0;2)	0.33	-0.44
Seyhun (1986)	1975-1981	U.S.	TD	(1;20)	1.1	-0.9
Our results (t-test)	**2018-2022**	**U.S.**	**RD**	**(0;1)**	**2.42**	**-0.21**
Our results (panel regression)	**2018-2022**	**U.S.**	**RD**	**(0;1)**	**2.70**	**-0.26**

Note: The table reports the previous literature's empirical results. The CAR (in percent) is presented over the event window. Trading day (TD) or Reporting Day (RD) is chosen as the Event Date.