CHANGES IN THE INSIDER TRADING SCENE DURING THE COVID-19 PANDEMIC

A COMPARATIVE STUDY OF INSIDER TRADING BEHAVIOUR BEFORE AND DURING COVID-19

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Abstract:

This thesis examines if insider traders have performed better during a working from home setting imposed by the Covid-19 pandemic during 2020-2021. Building on previous work from (Cohen, Malloy, & Pomorski, 2012), we identify trades as routine or non-routine. We find that non-routine trades on a 30-day basis on average outperform the market by 76 basis points when controlling for the effects of being in the industrial sector, and by 166 basis points when controlling for the effects of being in the information technology sector. Adding the aspect of WFH conditions in the market, the trades yield on average a 129 and 131 basis points higher return, depending on which industry is controlled for. We show that trades from the WFH period are indicative of higher abnormal returns, but we find no evidence to suggest that these differences can be attributed to that of non-routine insider trades.

Keywords:

Insider trading, Covid-19 Pandemic, Informative trading patterns, Working from home, Abnormal returns, Insider activity

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1. Introduction

The value that information provides for investors in the securities market cannot be overstated. Corporate insiders, who have insight into private information, are a coveted group among investors and possess somewhat of a competitive edge by virtue of this privileged access to information that is unbeknownst to the rest of market investors. Needless to say, understanding the behaviour behind insider trading and its informative value could provide investors with much needed aid in the pursuit to beat market averages. This holds especially true in times of crisis, such as the turbulent period that Covid-19 induced. This paper uses findings from (Cohen, Malloy, & Pomorski, 2012) in order to separate the insiders with predictive power from those that exclusively trade on routine. In doing so, we examine the changes in insider performance during the period affected by the Covid-19 pandemic, specifically during the timeframe when a large portion of people were working from the comfort of their homes.

During the late stages of 2019, a virus dubbed SARS-CoV-2, more commonly known as Covid-19, had an outbreak in the city of Wuhan, China. Covid-19 has since become widespread and as of the 11th of March, 2020, the World Health Organisation declared the classification of the virus as a global pandemic. This had devastating effects on the stock market and imposed working-from-home (WFH) conditions in many parts of the world. Sweden did not experience any forced lockdowns during the research period, but the Public Health Agency of Sweden has for long periods advocated working from home if possible. From Statistics Sweden (SCB), we learn that many organisations followed this recommendation and had many of their employees working at least partially from home during the period May 2020 to August 2021. This proposed significant changes in the insider trading scenes, as various corporations suffered from lack of an ability to monitor their employees' trading activities during this period. These circumstances provide an appealing landscape to research the activities of insider traders in order to better understand their behavioural patterns. This paper aims to unveil the behaviour of insider traders under the WFH conditions during the Covid-19 pandemic.

The first case of Covid-19 in Sweden was reported on January 19th 2020 in Jönköping, and later the first mortality was confirmed in Stockholm on March 11th. The first set of restrictions were put in place March 29th, which prohibited public gatherings of over 50 participants. The Swedish response to the pandemic has been both commended and vilified, due to its light restrictions in comparison to its neighbouring countries. Sweden avoided any forced lockdowns or penalties in order to bypass secondary effects and preserve the economy. In spite of this, Sweden had a large portion of the public working from home. Within the time period May 2020 - August 2021, the percentage of the public working from home ranged between 27 and 43 percent, topping out during the month of January 2021, as reported by SCB. As a consequence of the WFH setting, corporations with larger workplaces had to adapt due to the restrictions implemented. This in turn meant that the setting in which the people conducted their trading changed drastically.

This issue was highlighted in article by Palma and Franklin written in Financial Times in December 2021. The bank JP Morgan Chase was fined a record sum of 200 million US dollars in December 2021 due to being unable to log the messages on their personal devices, a direct consequence of the WFH conditions present at the time. Furthermore, Credit Suisse requested the authority to access personal phones of their employees in order to enforce more rigid surveillance on communication. This instantly made headlines by reason of being intrusive on their workers, but many banks were incentivised to follow their lead in pursuit of limiting the spread of sensitive information amongst bank employees. The management of insider information was a growing concern during the Covid-19 crisis and several banks feared to be hit by similar fines as with JP Morgan. In the five years spanning from september 2013 to September 2017, banks globally have disbursed approximately 375 billion US dollars in conduct fines, as reported by FMSB. This number is only expected to have grown during the period of WFH, as the risk of sensitive information spread and market manipulation is heightened when workers are working from the comfort of their home or away from the office.

The demand for information on insider trading patterns and behaviour is ample among investors. The literature on the informativeness of insider trading is plentiful and several of them conclude that the data suggests insiders earn abnormal returns in comparison to that of the average market investor [(Cohen et al., 2012) (Jeng, Metrick, & Zeckhauser, 2002) (Lakonishok & Lee, 2001) (Bettis, Vickrey, & Vickrey, 1997) (Knewtson, Sias, & Whidbee, 2010)]. Intuitively, this conveys the possibility that outside investors could benefit by replicating the aggregated insider trading portfolio based on readily available data. However, the strategic value of imitating insider trading patterns is not as forthright as one would think, and the results show that there are several hindering factors that prevent the replication of insider activity from being fruitful. For instance, (Lakonishok & Lee, 2001) find that insiders are mostly accurate in predicting small stock movements and less so in evaluating the change in larger stocks.

There is also the existing issue of regulating and detecting illegal trading, from the regulators point of view. Naturally, it is in their interest to better understand insider traders within different settings so that they can enforce their regulation more efficiently, regardless of the current market environment. The insider trading scene has been subject to a growing number of high profile cases in recent years, such as the SEC's investigation into the likes of the Galleon group in 2009 and Jeffrey Skilling, former CEO of Enron, in 2006. This implies that security regulators continue to invest considerable resources into the monitoring of insider activity. The literature from (Kallunki, Kallunki, Nilsson, & Puhakka, 2018) concludes that insiders with less wealth and income are more likely to engage in informed insider trading. This would suggest that the incentive to trade with private information could have been bolstered during the Covid-19 period due worse liquidity among households, consequently putting more pressure on financial supervisors and regulators.

With this study, we intend to research the potential gain from better understanding insider trading, under the implications of the Covid-19 pandemic. In doing so, we hope to capture if insider trading positively predicts future returns in a volatile market. Literature covering insider trading under such a market state is rather limited. The paper (Marin & Olivier, 2008) researched the predictive nature of insider trading in the scope of a financial crash, which yielded results that indicated that insider behaviour does indeed change during the period leading up to a financial crash. Although the crash in March 2020 induced by Covid-19 is different in nature and this paper deals with the period following the crash rather than the preceding period, we find comparable results that indicate that the behaviour and predictive power of abnormal stock returns are affected by the implications of the Covid-19 pandemic.

This thesis uses a framework, developed by (Cohen et al., 2012), that is able to surmise whether it is probable that an insider trade contains predictive information or not. By doing so, the aforementioned paper categorises two separate types of insider trades.

The first type of trade is referred to as "routine" insider trading, in which there is supposedly no inherent information regarding the future of the firm. These trades are predictable in their timing given the routine-like pattern of the traders themselves, and because of this they are likely to be trading for other reasons than possessing information about the firm's future. The other type of trade is categorised as "opportunistic" insider trading. This type of trade is sporadic in its nature and has no discernable pattern to its timing that can be observed. Due to this, opportunistic trades are more likely to contain valuable information on the future of the company and its performance.

The framework builds on the notion that insiders that trade by reason of possessing privileged information are less consistent in the timing of their trades. On the other hand, routine trades can be placed for a multitude of reasons that are predictable which in turn allows them to be detected by looking at the historical timing of the insiders previous trades. In example, routine sales are often motivated by diversification or liquidity needs that are not related to private information. These trades are usually executed in a routine-like manner. Routine buys can for example take place after an insider receives a bonus and decides to use it to buy company stock, since they are generally subject to discount-plans. Considering that bonuses are typically given out during a specific calendar-month, these trades are also conducted based on the routine of the insider.

To avoid confusion, this paper will label the two types of trades as routine and non-routine, respectively. Through sorting for these two types of insider trades, it becomes possible to somewhat accurately detect which of the trades within our dataset are informative and which ones are likely not. We achieve this in a similar fashion to the methodology used in (Cohen et al., 2012). That is, by looking into the history of insider traders in order to ascertain if there is a discernable pattern of each specific trader. If the insider has placed a trade during the same calendar-month for two or more years, between the years 1995-2021, then those trades following this pattern are considered routine. If there is no pattern to be found, or if a trade by an insider falls outside of their observable pattern, it is instead categorised as a non-routine trade. Note that this paper classifies on a trade-level, that is to say an insider can be both routine and non-routine at different points in time depending on their underlying trades.

By employing this methodology, we demonstrate that insiders perform significantly better in a WFH setting, when compared to that of a "normal" setting. In addition to this, we show that non-routine trades affects abnormal returns positively while routine ones achieve the opposite. Our regression analysis on a 30-day mean abnormal returns, when using WFH and non-routine as categorical variables as well as controlling for the effects of being in the industrial industry, showcase that trades placed in the designated WFH period perform better by 129 basis points ($t = 5.63$). Furthermore, non-routine trades have the same effect by 76 basis points ($t = 2.89$). We also back this data up by performing T-tests examining if the discrepancies are of significance. Between non-routine trades that are placed during the WFH time span versus those that are placed outside of said period, the difference in 30-day mean abnormal returns is as much as 103 basis points. This puts into perspective how large the margins are in between the periods. However, unlike our hypothesised outcome we find no evidence suggesting that non-routine trades benefit more relative to routine ones. In fact, the contrary seems to be true when examining 30-day abnormal returns. To conclude our findings, we show that WFH trades are indicative of higher abnormal returns but these differences are not attributed to non-routine trades.

We also check for industry specific effects, in which we find that the most notable sub-industries within our dataset, the industrial, IT and financial sectors, all display similar results that indicate insiders trading during the WFH period outperform their counterparts in terms of abnormal returns calculated on a 30-day basis. Lastly, we show that insider frequency has increased during the years plagued by the pandemic.

The contribution of this paper is twofold. Firstly, to build upon the literature of (Cohen et al., 2012) in order to further understand insider behaviour in circumstantial environments such as the pandemic. Secondly, to examine the predictive power of an informative trader when the market is highly volatile. This article aims to answer the research question: do insider traders perform better under WFH conditions, and more specifically if non-routine traders exhibit better performance.

2. Related literature

There are numerous studies looking into the behaviour of insider trading. (Jenter, 2005) sorts out the portion of insider trading that is uninformative by looking at behavioural patterns related to the value of their equity stakes. In a similar fashion, (Cohen et al., 2012) show that insider activity can be distinguished into either “routine” or “opportunistic” trades, and find that opportunistic insider activity serves as a strong predictor of future firm announcements and forecasts. Our thesis seeks to employ a similar methodology in dividing up the insider into two separate categories in order to extract the insider tradings with predictive power. The differing factor is that our paper will largely focus on the period where a considerable amount of people were working from home, because of the Covid-19 pandemic. In doing so, we broaden the scope of the research done by (Cohen et al., 2012) through applying the same idea in a vastly different setting.

The paper (Lakonishok & Lee, 2001) further contributes to the research on the informativeness of insider trades by examining how well the aggregate of insider trades predict market movements. The results support the notion that insiders do indeed have predictive value on market movements, but this is mainly driven by insider buys and in particular on smaller stocks. This notion that insider sales are less informative towards investors is commonly observed in the literature, for example [(Jeng et al., 2002), (Lakonishok & Lee, 2001), (Tavakoli, McMillan, & McKnight, 2012)]. However, contrary to this notion newer studies such as (Drobetz, Mussbach, & Westheide, 2020) and (Biggerstaff, Cicero, & Wintoki, 2020) find that both purchases and sales predict future abnormal returns.

Additionally, there are numerous accounting articles covering insider trades that are relevant to our study, but outside of our scope. For example (Ke, Huddart, & Petroni, 2003) show that insiders trade on knowledge of significant accounting disclosures up to two years prior to the disclosures. Another paper, (Kahle, 2000) finds that long-term performance of insider trading is closely linked to new security issuance.

A study by (Kallunki et al., 2018) investigates whether wealth and income matter in the decision to engage in insider trading. The conclusion that is arrived upon suggests that the higher the wealth and income of the insider, the lower the willingness to engage in insider trading. In a similar sense, (Marin & Olivier, 2008) finds that insider selling intensity peaks during periods leading up to a financial crash, in addition they also document that insider purchases seem to reach its highest point before a large increase in stock prices. In contrast, this paper targets the subsequent period from that of a financial crisis. It should also be noted that the crash induced by Covid-19 is vastly different in nature to those covered in previous literature, seeing as the predictive element of the crash could not have been derived from privileged information. Our focus is centred around identifying changes throughout the period of WFH restrictions caused by Covid-19, as opposed to singling out the insider intensity peaks.

Finally, (Jeng et al., 2002) approaches their research by using a performance-evaluation perspective, in which they find that insiders earn abnormal returns of over six percent per year on purchases. In terms of insider sales, there seems to be no significant abnormal returns to be observed. This approach differs from ours in that our thesis concentrates on the behaviour of individual insiders and the comparability of their performances during the time period preceding Covid-19 contra the subsequent period.

3. Data and Empirical Description

The data on insider trading used in this analysis was retrieved from the Swedish Financial Supervisory Authority database on insider trading. As in most countries, insider trading is regulated in Swedish law, in accordance with EU directives, and is required to be reported to the Swedish Financial Supervisory Authority. Traders subjected to the rules are persons “discharging managerial responsibilities and people closely associated with them” which is more closely defined in article 3.1.25 of the EU’s Market Abuse Regulation (MAR). The Swedish Financial Supervisory Authority provides an open online database on all trades stretching back to June 2016. Data covering all the trades from the year of 1995 is available at request, albeit the reporting standard during these years is slightly different. For this reason, we used data available dating back to January 1 2017 when calculating the returns and frequency of insider trading. However, when identifying routine and non-routine traders the dataset also included the period 1995 to 2016. This provided a bigger sample of insider traders, which resulted in a better predictive ability to identify which trades were routine based.

Using data from January 1 2017 until December 31 2021 results in 28,545 data points after cleaning. All data points with the status “Reviderad” or “Makulerad” (Revised or Retracted) have been erased, and transactions that happened outside of a marketplace have also been removed. This is due to the Swedish Financial Supervisory Authority invalidating the data themselves, and because the data reported outside of marketplaces was deemed liable to errors. Additionally, the focus is put on trades made in SEK, which covers the vast majority of what is reported. Finally, the analysis is limited to covering buy and sell transactions, avoiding instances when for example securities have been inherited, gifted or otherwise transferred without an active role of the insider in question. This allows for a focus on trades that follow an active participation by the person and also excludes the exercise of different stock options and alike from companies since this does not necessarily reflect changed incentives in the participation.

The computation of returns on all insider trades, occurring within the period spanning from January 1 2017 until December 31 2021, is based on stock price information (as close price per day) gathered from Refinitiv Eikon. In addition to the stock price history, we also used Refinitive Eikon to extract the market capitalization for each company in the dataset computed as the average market capitalization at the end of each year over the period we looked at. It was also used to collect GICS Sector codes and book to market ratios (as the latest available one). The data gathering was achieved by matching the ISIN codes retrieved from the Swedish Financial Supervisory Authority database. In replicating the portfolio of insiders, this study employs a buy-and-hold strategy of the aggregate insider tradings. When an insider buys, it is replicated by taking a long position in the stock. Alternatively, when the insider sells it is replicated by taking a short position. This fundamentally captures if the insider is bearish or bullish regarding the movement of the stock. The calculation method is the following: long position as $\ln(P_t/P_{t-1})$ and short position as $\ln(P_{t-1}/P_t)$. Where P_t is the close price of the transaction date + 30 or + 5 days, and P_{t-1} is the close price on the transaction date.

Following this, we calculate the market-adjusted returns of the insider traders by adjusting it to the returns of the index OMXSPI (also gathered from Refinitive Eikon). Furthermore, we compute the returns on both a 5- and 30-day basis. This is done in an attempt to capture the market reactions to the tradings of insiders, in order to gauge how long it takes for the informativeness of the insider trades to leak out to the market.

Using the literature from (Cohen et al., 2012), we divide insider traders into two separate groups of routine and non-routine. As described before, there are certain tendencies among insiders that provide the means to separate them into two sub-groups. Routine sales are most often done in an attempt to diversify or liquidate while routine buys oftentimes occur as a result of the trader receiving a bonus during a specific month of the year and being more likely to buy stocks in the company where they may have a discount plan. Therefore, routine trades are more likely to have a detectable pattern than that of non-routine.

We identify routine trades as ones where the trader has traded during the same calendar month for two or more distinct years, within the period spanning from 1995 to 2021. Non-routine trades encompass all the remaining trades, that is to say all trades where there is no distinguishable pattern for the trades made by the insider. One thing to note is that we allow for the trader to retain both routine and non-routine trades, in other words it is the trades themselves that are routine or non-routine. For instance, a trader that has traded in february for several years will have those trades categorised as routine. However, if that same trader has other trades that occur sporadically over the period, those will be categorised as non-routine trades, since they have no connection to the routine behaviour of the insider. Observe that this model is designed to approximate which trades are routine and which ones that are not. As a consequence, there is no guarantee that the classification of the trade is infallible. With that being said, the idea of this model builds on the notion that informatively driven trades are more likely to be inconsistent in their timing than that of routine trades. As such, the model should on average detect which trades are routine, and in doing so subsequently find the trades that are non-routine by process of elimination.

In addition to classifying the insiders into routine and non-routine traders, we also separate them based on which period they placed their trades in. This yields insight into whether the trades were executed during a period where WFH was prominent or not. By doing so, we form a set of four distinct groups subject to analysis in this study. These being:

- WFH routine
- WFH non-routine
- No-WFH routine
- No-WFH non-routine

For the WFH statistics we used data reported by SCB. The reports show that between 27 to 43 percent worked at least partially from home during the timeframe May 2020 to August 2021. It is worth noting however, that the regional differences were quite notable. For instance, in the region of Stockholm the portion working from home was larger. During the third quarter of 2020 the percentage of people working from home in

Stockholm was 52 percent, this metric later peaked in the first quarter of 2021 at 62 percent. This indicates that the share of people working from home was much larger in densely populated areas where the offices could not safely accommodate all employees. The amount of employees working from home was especially large in the IT and financial industries. Statistics Sweden report that within the financial industry 48 to 61 percent of personnel worked from home in-between the third quarter 2020 and the second quarter 2021, for the IT sector the corresponding percentages ranged from 77 to 87 percent. This effect was even greater amongst positions that necessitates higher forms of education. Reportedly, within professions that require advanced university competence, specifically in economics and management, approximately 70 to 89 percent of employees worked from their homes during the designated WFH period. SCB reports that the financial and information technology sectors were among the industries with the highest percentage of workers working from home.

The trades that are denominated with the WFH title are those that are placed within the time span May 2020 to August 2021, as this period was subject to a higher degree of WFH restrictions. While we cannot guarantee that all the traders in the respective periods worked either from home, or in-office, there is sufficient evidence that suggests that the portion of traders working from home during the designated WFH-period was significantly larger than in the No-WFH period. As such, we theorise that this constitutes a setting in which the information flow in the world is increased and in turn more influential on the trades of insiders. Working from home, at least partially, would allow the workers to more freely engage in spreading as well as acting on private information. Comparing these groups should give us insight into how the behaviour and performance of insiders has changed during a period in which many of them worked while being subject to less monitoring. Adding the routine factor to this comparison further expands on these results as it gives us an understanding of which type of insider this trade is driven by.

Table I
Summary Statistics

In this table we find the summary statistics for the sample that has been used in this study. The dataset contains all the insider trades that have been reported to the Swedish Financial Supervisory Authority from January 1 2017 until December 31 2021. Note however that when identifying the routine trades, data spanning back to 1995 was used, also retrieved from the Swedish Financial Supervisory Authority. Routine trades are defined as those where a discernible pattern in the timing of the trade made by the same insider can be identified, i.e. if the insider places a trade in the same calendar month for at least two years. All trades that follow the given pattern of its insider are categorised as routine. Non-routine trades are simply all the remaining insider trades that did not fall under the category of routine. For example, if Insider A places one or more trades in March during three separate years, those trades would be considered routine. However, if that same insider places a trade in September during one of those years, it would be considered non-routine. Trades that are conducted within the period May 1 2020 to August 31 2021 are designated as WFH (working from home). The rest of the trades that are outside of this timeframe are instead classified as No-WFH, this includes trades conducted from January 1 2017 until April 31 2020 and from September 1 2021 up until December 31 2021.

	No. of		**Precentage**
Unique insiders	5 277		
Routine trades	3 370	% of trades that are routine	11.81%
Non-routine trades	25 175	% of trades that are non-routine	88.19%
WFH trades	7 944	% of trades that are WFH	27.83%
No-WFH trades	20 601	% of trades that are No-WFH	72.17%
Total trades	28 545		
Unique companies	1 120		
Trades/insider	5.41		
Companies/insider	0.21		

4. Empirical Findings

4.1. Performance of No-WFH versus WFH Trades

In this section we analyse the differences in performance of the trades made during the WFH period contra those made outside of said period. The aim is to uncover whether there are any significant differences between the groups and if so, what are the driving factors for these discrepancies. In order to do so, we employ the method of classifying traders into routine and non-routine so that we compare them against each other.

Table II

Summary Statistics on Non-Routine vs Routine During No-WFH and WFH

This table summarises the statistics of 30 and 5 days mean abnormal returns including all trades for routine versus non-routine during both WFH and No-WFH periods. The trades marked as No-WFH are those conducted between January 1 2017 and April 31 2020, as well as those executed from September 1 2021 up until December 31 2021. Conversely, WFH trades are placed in between May 1 2020 and August 31 2021, this time span signifies a period in which a significant portion of the working population were working at least partially from home. Routine trades are defined as trades that follow an observable pattern of the insider behind them. Non-routine trades comprise all remaining trades, in other words where the timing of the trades cannot be traced to the routine of the insider. All returns are market adjusted using OMXSPI. It also displays the p-value of the T-tests that serves to examine the differing mean returns of two distinctive groups of trades.

	Non-Routine		**Routine**	
	No-WFH	**WFH**	**No-WFH**	**WFH**
Mean 30-Day Return	0.24%	1.27%	-3.02%	2.39%
Standard Deviation	16.2%	16.8%	11.5%	15.8%
T-test p-value	*0.000008532*		*< 0.00000000000000022*	
Mean 5-Day Return	0.92%	1.24%	0.11%	0.52%
Standard Deviation	7.69%	8.84%	5.47%	5.65%
T-test p-value	*0.004653*		*0.05819*	
Count	18 116	7 059	2 485	885

From computing the 30 and 5-day mean abnormal returns, for both routine and non-routine trades during WFH and No-WFH, we can draw the conclusion that insiders trading during WFH periods earn a higher return compared to No-WFH. The lowest mean return is found within the routine traders during No-WFH and the best in routine traders during WFH. Both these indications are in line with our hypothesis as well as theories established in previous papers. Looking at the results, WFH conditions seem to have improved the performance of all groups, but especially so routine insiders. In fact, routine traders are outperforming non-routine traders in some aspects as the group routine WFH exhibits the highest return within the sample. This does somewhat contrast the finding of (Cohen et al., 2012). However, as can be seen by the table contents, the portion of routine insider trading on the Swedish markets is significantly smaller than that of the American securities market. This could serve as the explanation for the differences in our findings.

Another noteworthy observation is that the portion of non-routine traders, within the subsequent periods, is somewhat equally distributed. Non-routine insider trades encompasses about 88 percent of total insider trades in the No-WFH period, whilst it makes up approximately 89 percent during the WFH period, only a slight increase.

Table III

Summary Statistics on Non-Routine vs Routine During No-WFH and WFH on Buy and Sell Orders

This table compiles the 30 and 5 days mean abnormal returns for routine versus non-routine trades divided into buy and sell orders, during both working from home and not working from home periods. The classification of WFH and routine follows the same standards as in Table I. The return of the buy orders are calculated by taking the natural logarithm of longing the stock for 30 and 5 days starting from the transaction date. For sell order the return is calculated by taking the natural logarithm of shorting the stock for 30 and 5 days starting from the transaction date. The exact calculations are the following: long position as $ln(P_t/P_{t-1})$ and short position as $ln(P_{t-1}/P_t)$. Where P_t is the transaction date + 30 or 5 days, and P_{t-1} is the transaction date. Furthermore, all returns are market-adjusted using OMXSPI.

	Non-Routine				**Routine**			
	No-WFH		**WFH**		**No-WFH**		**WFH**	
	Buy	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
Mean 30-Day Return	-0.97%	3.54%	0.70%	2.65%	-2.04%	-6.27%	2.01%	3.74%
Standard Deviation	14.40%	19.80%	15.60%	19.40%	11.15%	12.10%	17.60%	5.86%
Mean 5-Day Return	0.58%	1.86%	1.19%	1.37%	-0.18%	1.05%	0.30%	1.31%
Standard Deviation	7.49%	8.13%	8.01%	10.6%	5.68%	4.60%	6.06%	3.77%
Count	13 261	4 855	5 022	2 037	1 913	572	690	195

Looking more closely at the data and separating the trades into buy and sell orders, it becomes apparent that the amount of buy orders outweigh sell orders. The buys follow the same trend as when looking at the total mean return, as it can be seen to be more profitable during the WFH period in all instances. The sales however implicate a slightly different scenario, and is more inconsistent in its pattern. Non-routine insider trades exhibit lower abnormal returns during the WFH period, when looking exclusively at sales. This is true for both 30-day and 5-day returns. The opposite effect is observed for routine insider sales, seeing as they are significantly higher in the WFH period, both when it comes to 30-day and 5-day returns.

Table IV
T-test: No-WFH vs WFH

This table showcases a T-test that examines whether the mean abnormal returns differ between the No-WFH and WFH groups of the dataset for 30 and 5 day returns, counting from the transaction date of the trade. The mean return includes all trades within our dataset that is made within each respective time-period and is calculated by including both buys and sales. The classification of WFH and No-WFH are the same as in Table I. The trades marked as No-WFH are those conducted between January 1 2017 and April 31 2020, as well as those executed from September 1 2021 up until December 31 2021. Trades categorised as WFH are all remaining trades within our sample, that is to say trades placed in between May 1 2020 and August 31 2021. All returns are market adjusted using OMXSPI.

30-Day Market Adjusted Return		**5-Day Market Adjusted Return**	
t = -7.2941, df = 28475, p-value = 0.0000000000003085		*t = -3.2758, df = 28475, p-value = 0.001055*	
Mean in Group No-WFH	**Mean in Group WFH**	**Mean in Group No-WFH**	**Mean in Group WFH**
-0.15%	1.39%	0.82%	1.16%

First off, in our examination T-tests are used to determine if the separate groups display differences in their means with statistical significance. To start with, we look at the difference in mean returns of trades executed during the No-WFH versus the WFH period. The testing is done both on a 30-day and a 5-day basis in order to gauge the differences in timeframe. Both buys and sales are included in the total return as the main purpose of this test is to analyse whether or not there is a discrepancy between the groups that can be of interest to examine. The results are included in Table IV. Comparing all trades during No-WFH and all trades during WFH, we find that the means are significantly different, with a p-value of 0.000 for 30-day return and a p-value of approximately 0.001 for 5-day return (see Table IV). This clearly illustrates that insiders earned a higher return under WFH conditions. The insider transition from underperforming the market by 0.15 percent to outperforming it by 1.39 percent, 30 days after the transaction day. A similar effect can be observed when comparing the returns 5 days after that of the transaction date, although the differences are smaller in this scenario. Results from the initial T-test indicate that there is a difference to be observed and is worthwhile investigating, as the T-test illustrates that the WFH mean return is significantly higher than the mean return of the No-WFH group.

Next we look at tests that showcase results on whether or not non-routine trades exhibit any performance differences within and outside of the WFH time span. The hypothesised outcome of the study was that non-routine trades placed during the WFH period, would differ and outperform non-routine trades placed during No-WFH. The result found supports this belief, as once again we find that the return spread is considerably large and significant for both the 30 and 5-day returns, with a respective p-value of 0.000 and 0.005 (see Table II). As can be seen from above testing, the findings once more point toward there being a discrepancy in between the two time periods, this time limiting the pool of trades to only those that are considered non-routine. The data shows that non-routine insiders during the WFH period earn 30-day abnormal returns of 127 basis points, which exceed the 30-day abnormal returns earned by non-routine insiders outside of this period by 103 basis points. Results on 5-day returns show similar indications, although the effects are once again less divergent.

As touched upon previously in this paper, one probable contributor to this occurrence is the monitoring issue present during WFH. The non-routine traders are given more freedom and time in conducting their insider trades. This means that not only is the flow of private information likely to be more apparent during WFH, but the traders themselves are also expected to have more time to process and act upon the collected information, due to the time saved as a consequence working from home. Furthermore, if it takes more than 5 days for the information to leak to the public market, this could explain why the results of the 30-day returns are more telling than that of the 5-day return testing.

Next we look at tests that intend to uncover whether or not routine-like trades exhibit any performance differences within and outside of the WFH time span. This will shed light upon if trades that are less likely to be based on information also exhibit any changes as a consequence of the WFH setting. The results regarding this are also showcased in Table II.

In the case of routine traders, the intuitive fallout would be that the groups WFH and No-WFH should not differ too much in their mean returns, as they do not benefit as much from increased information flow due to WFH conditions. This however is not the case according to our tests. We find that routine trades also perform significantly better in a WFH setting, this is true within the tests for both 30 and 5-day returns with a p-value of 0.000 and 0.100, respectively (see Table II). Worth noting however is that the results differ drastically between 30-day and 5-day returns, with the latter being far less significant. As demonstrated, the increase in abnormal 30-day returns are quite drastic. In fact, it marks the biggest spread in returns that stem from comparing No-WFH and WFH, in our dataset. This could be attributed to a number of reasons. Looking at Table III, we can see that it is primarily the sales that are driving this increase in return after the inception of WFH. Given that the sample of sell orders by routine insiders during the WFH period is the smallest in our dataset, this could have a notable impact on the result. Buy orders can also be observed to have performed better under WFH conditions.

The T-tests performed seem to indicate that there is indeed an effect stemming from the period where the portion of the working population that worked from home was more abundant. It is not clear however if the non-routine insiders are the main beneficiaries from this change, since the routine insider trades also display higher abnormal returns following the inception of Covid-19, and along with its WFH implications

4.2. Baseline Regression

To further augment our analysis, we complement the findings from the T-tests with regressions in pursuit of delving deeper into the impact and driving factors of the changes observed during the duration of WFH. We run linear regressions on the abnormal mean return on a 30 and 5-day basis, with the explaining variables Non-Routine, WFH and Interaction. The natural logarithm of the firm's market cap (in million SEK) and the natural logarithm of the firm’s book to market ratio is used as control variables. As indicated below, we also include month fixed effects. The results of the regressions are found below in Table V and VI, for 30 and 5-day returns, respectively.

Table V
Regression on 30-Day Mean Abnormal Return

*This table showcases a regression analysis on the determinants of returns given by routine and non-routine insider trades. The time period looked at spans from January 1 2017 up until December 31 2021. The dependent variable in this regression is the 30-day mean abnormal returns starting from the transaction day. The classification of routine and non-routine trades are the same as reported in Table I. In short, routine trades are defined as trades in which the given insider has established a detectable pattern by trading during the same calendar-month for multiple years. If the trade matches that pattern, it is considered routine. Non-routine trades make up the remaining trades within our data sample, on the premise that they cannot be linked to any routine behaviour. Non-routine is a dummy variable given the value one if the trade is categorised as non-routine, and zero otherwise. WFH is a categorical variable equal to one if the trade is placed within the time period May 1 2020 to August 31 2021, and zero if it is placed outside of this timeframe. Industrial and IT are also categorical variables checking for if the given firm's GICS code matches the respective sectors, Industrial and IT. Interaction is a dummy variable that controls if the trades were both non-routine and placed during WFH, if true it is given the value of one, and zero otherwise. Market cap, in million SEK, and book to market ratio are used as control variables. Both variables are given by the natural logarithms of market capitalisation and book to market ratio, correspondingly. We also control for fixed month effects, these are included in each even number Column. The t-statistics are stated in parenthesis below the measured estimates. Significance-levels; 0.1%, 1%, 5% and 10% are reported with the indicators; "***", "**", "*" and ".", respectively.*

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Non-Routine	0.79**	0.76**	1.93***	1.90***	1.72***	1.66***	2.85***	2.80***
	(3.07)	(2.89)	(7.11)	(7.05)	(6.59)	(6.28)	(10.47)	(10.36)
WFH	1.49***	1.29***	5.23***	5.07***	1.51***	1.31***	5.25***	5.08***
	(6.74)	(5.63)	(8.98)	(8.74)	(6.79)	(5.70)	(9.03)	(8.78)
Industrial	-2.14***	-2.08***	-2.14***	-2.09***				
	(-9.43)	(-9.26)	(-9.47)	(-9.30)				
IT					-1.40***	-1.41***	-1.41***	-1.42***
					(-5.52)	(-5.58)	(-5.57)	(-5.62)
Interaction			-4.26***	-4.31***			-4.26***	-4.30***
			(-6.74)	(-6.82)			(-6.76)	(-6.83)
Market Cap	-0.21***	-0.20***	-0.21***	-0.19***	-0.32***	-0.30***	-0.32***	-0.30***
	(-5.05)	(-4.61)	(-5.00)	(-4.54)	(-7.88)	(-7.38)	(-7.85)	(-7.33)
Book to Market Ratio	-0.22*	-0.26**	-0.23**	-0.27**	-0.22*	-0.26**	-0.23*	-0.27**
	(-2.46)	(-2.88)	(-2.59)	(-3.00)	(-2.38)	(-2.88)	(-2.51)	(-3.01)
Fixed Effect		Month		Month		Month		Month
Number of observations	28 545	28 545	28 545	28 545	28 545	28 545	28 545	28 545

4.2.1. Results from 30-day Regression

The table above presents the results from our first test which runs a regression with regard to the 30-day mean abnormal return of the insiders in our dataset. The main purpose of the regression is to examine the impact of the three initial variables, namely: Non-Routine, WFH and Interaction. We also control for other factoring elements in stock returns such as market cap (in millions SEK) and book to market ratio. In addition to this, the industries with the biggest sample sizes in our dataset are included separately, these are Industrial and IT (Information Technology). Lastly we include month fixed effects, it is designated in which Columns this is included. The routine behaviour of insiders are determined on a trade-level, this means that it is the trades themselves that are considered routine or non-routine. As a consequence, any given insider can be both routine and non-routine at different points in time depending on their underlying trading behaviour.

Column 2 and 6 found in Table V constitute our analysis covering the impact of non-routine trades and the WFH period on abnormal returns. In Column 2 we find that non-routine trades are significant on a 1% level. It also showcases that non-routine insiders earn an additional 76 basis points (t = 2.89) on abnormal returns 30 days following the date that the trade was made. This holds true when controlling for the effects of being in the Industrial sector (GICS Sectors, see appendix). Whether or not a trade was made during the WFH period seems to be predictive of abnormal returns on a 0.1% significance-level. Insider trades within this period yield additional returns of 129 basis points (t = 5.63) after 30 days.

In Column 4 we include the variable Interaction which serves to test the interactive effect of trades that fulfil both criterias of being traded during WFH and being classified as non-routine. The coefficient of the interactive variable of WFH and non-routine trades indicate that the abnormal returns are negatively affected by 431 basis points (t = -6.74) when compared to all WFH trades. This demonstrates that the increase in 30-day abnormal returns of WFH trades are mainly driven by routine traders. This is also illustrated in Table II where we can observe that 30-day mean abnormal returns increase by 541 basis points for routine trades while the increase is only 103 basis points for non-routine traders, when comparing WFH trades to those that are not.

If we instead direct our focus on the results in Column 6, when we control for working in the IT sector (GICS sectors, see appendix), non-routine trades are in this case significant on a 0.1% level instead. The returns of the trades designated as non-routine are 166 basis points (t = 6.28) higher on a 30-day basis. In the case of trades during the WFH period, they are shown in Column 6 to be indicative of 30-day abnormal returns with 0.1% significance and earn additional returns of 131 basis points (t = 5.70). Similarly to the results in Column 4, Column 8 also reports that the interaction of WFH and non-routine trades impact abnormal returns negatively, this time by 430 basis points (t = -6.83) and again with 0.1% significance.

In summary, the data presented seem to point toward both non-routine and WFH being strong predictors of future 30-day abnormal returns. However, the results stemming from the interaction of these two variables show that routine trades are more of a beneficiary from the implications of WFH. Furthermore, neither of the two industries have any positive correlation with increased return in our regression analysis. In fact, they seem to have a negative impact with regard to 30-day abnormal returns. Again, the difference in 30-day abnormal returns between the WFH and No-WFH period is quite large and proven to be significant by both the regression analysis and the T-test (see Table II).

Table VI
Regression on 5-Day Mean Abnormal Return

*This table showcases a regression analysis on the determinants of returns given by routine and non-routine insider trades. The time period looked at spans from January 1 2017 up until December 31 2021. The dependent variable in this regression is the 5-day mean abnormal returns starting from the transaction day. The classification of routine and non-routine trades are the same as reported in Table I. In short, routine trades are defined as trades in which the given insider has established a detectable pattern by trading during the same calendar-month for multiple years. If the trade matches that pattern, it is considered routine. Non-routine trades make up the remaining trades within our data sample, on the premise that they cannot be linked to any routine behaviour. Non-routine is a dummy variable given the value one if the trade is categorised as non-routine, and zero otherwise. WFH is a categorical variable equal to one if the trade is placed within the time period May 1 2020 to August 31 2021, and zero if it is placed outside of this timeframe. Industrial and IT are also categorical variables checking for if the given firm´s GICS code matches the respective sectors, Industrial and IT. Interaction is a dummy variable that controls if the trades were both non-routine and placed during WFH, if true it is given the value of one, and zero otherwise. Market cap, in million SEK, and book to market ratio are used as control variables. Both variables are given by the natural logarithms of market capitalisation and book to market ratio, correspondingly. We also control for fixed month effects, these are included in each even number Column. The t-statistics are stated in parenthesis below the measured estimates. Significance-levels; 0.1%, 1%, 5% and 10% are reported with the indicators; "***", "**", "*" and ".", respectively.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-Routine	0.46***	0.42***	0.49***	0.46***	0.60***	0.57***	0.63***	0.61***
	(4.02)	(3.63)	(3.81)	(3.51)	(5.51)	(5.16)	(5.10)	(4.84)
WFH	0.21*	0.33**	0.32	0.44*	0.22*	0.33**	0.33	0.45*
	(1.97)	(2.87)	(1.45)	(1.99)	(2.05)	(2.94)	(1.51)	(2.03)
Industrial	-0.27*	-0.30**	-0.27*	-0.30**				
	(-2.54)	(-2.82)	(-2.54)	(-2.82)				
IT					-0.50***	-0.46***	-0.50***	-0.46***
					(-3.90)	(-3.53)	(-3.90)	(-3.53)
Interaction			-0.12	-0.13			-0.12	-0.13
			(-0.47)	(-0.51)			(-0.50)	(-0.52)
Market Cap	-0.11***	-0.11***	-0.11***	-0.11***	-0.14***	-0.13***	-0.14***	-0.13***
	(-5.54)	(-5.27)	(-5.54)	(-5.26)	(-6.81)	(-6.51)	(-6.81)	(-6.51)
Book to Market Ratio	-0.17***	-0.17***	-0.17***	-0.17***	-0.18***	-0.17***	-0.18***	-0.18***
	(-3.67)	(-3.57)	(-3.67)	(-3.57)	(-3.82)	(-3.71)	(-3.83)	(-3.71)
Fixed Effect		Month		Month		Month		Month
Number of observations	28 545	28 545	28 545	28 545	28 545	28 545	28 545	28 545

4.2.2. Results from 5-day Regression

Table VI presents the regression results on a 5-day mean abnormal return basis. In this case, the logarithm of market cap (in millions SEK) and the book to market ratio of the companies are used as control variables and regressions are made including both the Industrial sector (GICS sectors, see appendix) and the IT sector. We included month fixed effects where indicated. Columns 2 and 6 illustrate a significant positive correlation on mean abnormal returns for non-routine insiders as well as for trades made during the WFH period. Observing the non-routine variable, it is significant at a 0.1% level. Looking at Column 2, non-routine trade yields a 42 basis points (t = 3.63) higher return relative to other trades 5 days after the trade was made. This holds true when controlling for the effects of being in the Industrial sector. If the trade was made during the WFH period, the trade yielded an additional 33 basis points (t = 2.87) after 5 days at a 1% significance level. If the trade was made by an insider within the Industrial sector, the trade yielded a 30 basis points (t = -2.82) lower return on average at a 1% significance level.

Looking at Column 6, we instead include the IT sector where we previously included the Industrial sector (GICS sectors, see appendix). In this regression, the non-routine insiders earned a higher abnormal return of, on average, 57 basis points (t = 5.16) 5 days following the transaction date of the trade at a 0.1% significance level. Additionally, the WFH aspect had the same contribution as the previous regression, yielding a 33 basis point (t = 2.94) higher average mean abnormal return at a 1% significance level. An insider trade, performed by someone in the IT sector, on average underperformed the market and earned a 46 basis point (t = -3.53) lower abnormal return at a 0.1% significance level.

Column 4 and 8 showcases the interactive value of WFH and non-routine. As opposed to the 30-day abnormal return regression (see Table V), the results from the regression analysis on a 5-day basis is not significant. We find that the interaction of WFH and non routine affect abnormal 5-day returns negatively by 0.13 (-0.52) basis points, regardless of which industry we control for. This demonstrates that the increase in 5-day abnormal returns is driven somewhat equally across routine and non-routine trades.

The table illustrates that non-routine trades earn a higher average mean abnormal return compared to routine trades, see Column 2 and 6, on a 5-day basis. Moreover, the WFH period, with its new market conditions, had a positive impact on the return of insiders. The two industries we looked at showed no positive impact on the average mean abnormal return, instead they showed a negative correlation. We find no evidence that non-routine trades are the main beneficiaries from conditions imposed by WFH standards.

4.3. Cross-Industry Analysis

In this segment, the effects of belonging to a certain sector is examined. The purpose of this is to determine if certain industries exhibit particularly high margins. As before, trades are divided into groups of WFH and No-WFH, as well as routine and non-routine. Industries with especially high frequency of trades and WFH percentages will be taken more into account as per their significance to the data.

As can be seen in Table VII below, companies belonging to the Industrials and Information technology (IT) sectors were traded on with the highest frequency, during the researched period. Taking a closer look at the returns of these industries, we find that nearly all groups performed better during the period of WFH, with the exception of 5-day abnormal returns of non-routine insiders in the industrials sector. As mentioned in the data description section of this thesis, the IT industry was the sector with the highest portion of workers conducting their work from home, ranging from 77 to 87 percent throughout different quarters of 2020 and 2021 (see appendix). The data on WFH statistics from SCB does not include an equivalent for the GICS industrial sector. The closest match included was the *"manufacturing of engineering goods"* industry, which exhibited WFH percentages similar to that of the national standard.

Another sector with particularly high WFH percentages, when compared to the national standard, is the Financial sector. The frequency of trades within this sector was moderate but its ratio of WFH to No-WFH trades were relatively high, as illustrated in Table VII. Inspecting the abnormal returns of the Financial industry, we find similar observations as with aforementioned industries. That is to say, WFH trades outperform No-WFH trades across the spectrum, especially non-routine trades. This could serve to validate the theory presented in several articles, that the impaired monitoring capabilities in the Financial industry impacts the incentive to trade on private information. Companies belonging to the health care sector were also frequently traded during the studied period, and represent one of the few industries in which No-WFH trades perform better than that of WFH trades.

Table VII

Summary Statistics on GICS Sector Level

The following table presents a summary of statistics specific to the featured sector. The classification was made by employing GICS Sector codes for each company included in our dataset and collecting the data from Refinitive Eikon. For more information about which companies are included in each sector, refer to the appendix. The categorisation of routine behaviour as well as WFH and their respective counterparts are as defined as in Table I. Mean 30-day and 5-day abnormal returns are calculated as the average market-adjusted return using OMXSPI as a basis. Count represents the number of trades conducted within each corresponding sector.

	Communication Services				**Consumer Discretionary**				**Consumer Staples**			
	Non-Routine		**Routine**		**Non-Routine**		**Routine**		**Non-Routine**		**Routine**	
	No-WFH	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**
Mean 30-day Return	3.91%	0.89%	-2.82%	2.47%	1.21%	4.39%	-1.21%	1.62%	-2.76%	-2.87%	0.56%	2.82%
Standard Deviation	27.64%	16.74%	12.23%	12.72%	15.10%	15.61%	11.85%	8.07%	14.10%	8.60%	7.82%	8.78%
Count	770	282	42	14	2 087	723	133	33	737	167	56	17
Mean 5-day Return	1.62%	2.04%	0.83%	1.68%	1.06%	3.48%	0.48%	1.14%	-0.18%	-1.04%	0.60%	2.53%
Standard Deviation	10.37%	8.48%	3.80%	8.15%	6.38%	9.62%	7.69%	2.48%	5.78%	4.09%	3.71%	3.74%
Count	770	282	42	14	2 087	723	133	33	737	167	56	17

	Energy				**Financials**				**Health Care**			
	Non-Routine		**Routine**		**Non-Routine**		**Routine**		**Non-Routine**		**Routine**	
	No-WFH	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**
Mean 30-day Return	11.86%	8.32%	12.18%	18.57%	0.92%	3.32%	-0.71%	1.60%	2.25%	1.97%	0.54%	-1.17%
Standard Deviation	19.11%	20.13%	11.48%	1.57%	11.30%	16.21%	7.70%	17.12%	16.74%	18.40%	11.62%	9.56%
Count	222	35	5	2	868	567	154	38	3 234	1 067	124	34
Mean 5-day Return	-0.38%	-1.03%	-1.15%	3.68%	0.54%	2.72%	-0.07%	1.14%	1.93%	1.67%	1.52%	2.09%
Standard Deviation	11.25%	11.40%	2.53%	0.77%	5.54%	9.22%	3.10%	6.68%	8.39%	8.82%	7.31%	7.16%
Count	222	35	5	2	868	567	154	38	3 234	1 067	124	34

	Industrials				**Information Technology**				**Materials**			
	Non-Routine		**Routine**		**Non-Routine**		**Routine**		**Non-Routine**		**Routine**	
	No-WFH	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**
Mean 30-day Return	-1.76%	0.04%	-4.09%	3.11%	-1.39%	1.29%	-2.40%	1.36%	0.38%	1.70%	0.22%	-0.73%
Standard Deviation	13.96%	17.24%	12.05%	18.04%	15.53%	17.34%	10.66%	8.05%	13.74%	19.83%	6.85%	8.17%
Count	3 886	1 533	1 632	582	3 638	1 607	226	115	502	290	47	14
Mean 5-day Return	0.78%	0.30%	0.18%	0.31%	0.68%	1.12%	-1.52%	0.25%	0.11%	-0.14%	0.61%	1.55%
Standard Deviation	6.90%	8.14%	5.22%	5.94%	8.40%	10.28%	6.76%	4.56%	5.75%	7.52%	4.62%	3.63%
Count	3 886	1 533	1 632	582	3 638	1 607	226	115	502	290	47	14

	Real Estate				**Utilities**				**Unidentified**			
	Non-Routine		**Routine**		**Non-Routine**		**Routine**		**Non-Routine**		**Routine**	
	No-WFH	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**	**No-WFH**	**WFH**
Mean 30-day Return	0.78%	-0.38%	-0.59%	-0.44%	0.25%	-0.61%	-0.15%	-2.57%	1.14%	-3.54%	-1.45%	-2.45%
Standard Deviation	8.69%	10.74%	5.82%	7.53%	16.54%	12.17%	2.17%	0.59%	24.10%	17.16%	6.23%	3.13%
Count	1 217	530	44	27	109	68	7	3	846	190	15	6
Mean 5-day Return	0.61%	0.75%	-0.15%	-0.18%	2.01%	-0.29%	-0.50%	-0.20%	0.25%	-0.24%	-0.22%	0.60%
Standard Deviation	6.27%	5.18%	3.29%	2.55%	6.61%	4.93%	2.13%	1.21%	9.65%	8.50%	3.70%	4.58%
Count	1 217	530	44	27	109	68	7	3	846	190	15	6

4.4. Frequency of Trades

In the following section we shed light on the frequency of trades (as number of trades) and the amounts traded in our dataset. While our main focus is on the returns earned during the period, we believe this serves to illustrate the change of nature on the insider trading scene in Sweden during the Covid-19 pandemic and the subsequent WFH period.

Table VIII

Summary Statistics on Frequency and Sum

This table shows a summary on the number of sell and buy orders and the corresponding trading volumes in our dataset in part A. The time period looked at spans from January 1 2017 up until December 31 2021. Due to the risk of reporting errors and lack of control conducted at the Swedish Financial Supervisory Authority, the summary amounts are controlled with the Holdings.se database, widely used in the Finance business community in Sweden, and considered plausible. Furthermore, in part B, summary statistics on the number of sell and buy orders for non-routine and routine trades respectively are shown. The classification of WFH and routine as well as their counterparts are the same as in Table I. Finally, in C, it shows the monthly average number of sell and buy orders during the No-WFH and WFH period respectively in our dataset.

A. Yearly Buy and Sell Frequency and Sum

Year	# of Sell	SEK Sell	# of Buy	SEK Buy
2017	1 128	2 963 718 631	2 785	13 223 255 419
2018	1 329	2 396 162 873	3 568	15 892 877 653
2019	1 345	5 872 328 327	3 959	7 946 264 137
2020	2 312	4 989 195 931	4 799	9 127 225 326
2021	1 545	9 227 451 008	5 775	19 698 064 223

B. Buy and Sell Frequency on Non-Routine vs. Routine

	Non-Routine		Routine	
Year	# of Sell	# of Buy	# of Sell	# of Buy
2017	1 020	2 372	108	413
2018	1 228	2 956	101	612
2019	1 217	3 451	128	508
2020	1 976	4 241	336	558
2021	1 451	5 263	94	512

C. Average Number of Sell and Buy Orders No-WFH vs. WFH

	Average # of Sell	Average # of Buy
No-WFH	123	345
WFH	140	357

Looking at Table VIII, from the years of 2017 to 2021 the amount of sell orders went from 1,128 to 1,545, an increase of 37 percent, and buy orders went from 2,785 to 5,775, an increase of 107 percent, in our dataset. The sell orders increased by a staggering 211 percent with the amounts going from around 3 billion SEK in 2017 to around 9 billion SEK in 2021. The corresponding number for buy orders was around 13 billion SEK in 2017 and 20 billion SEK in 2021, an increase of 49 percent.

As shown in Table VIII, non-routine insiders went from conducting an average of 1,155 sell orders in between 2017-2019 to an average of 1,714 during 2020-2021, an increase of about 48 percent. The corresponding number of average buy orders went from 2,926 in 2017-2019 to 4,752 in 2020-2021, an increase of 62 percent. In contrast, routine insiders' average number of sell orders went from an average of 112 in 2017-2019 to 215 in 2020-2021, representing a change of around 91 percent. The buy orders for routine insiders went from an average of 511 in 2017-2019 to an average of 535 in 2020-2021, a slight increase of 5 percent. Looking at the numbers, it is rather clear that the pandemic did change the environment for insider trading in Sweden. With that being said, the differences are somewhat insignificant and can hardly yield any conclusions, given that the differences are negligible and non-routine traders have a larger representation in our universe of insiders.

Looking more specifically on the change in frequency of trades during the WFH period and No-WFH period, Table VIII showcases a change. In the 44 months of No-WFH the average amount of sell orders per month in our dataset was 123. This number increased to an average of 140 sell orders during the 16 months of WFH, representing a 14 percent increase. Looking at the buy orders, they went from an monthly average of 345 during the No-WFH period to a monthly average of 357 during WFH, a rise of 4 percent.

We can see a slight change of behaviour during the period with the data indicating that insiders traded more frequently and for greater amounts of money during this pandemic. We cannot, nor is it our ambition, to draw any clear conclusions on the topic of frequencies and volumes. However, as the data suggests, this could be a topic of interest in future studies.

5. Concluding Remarks

This paper studies the behaviour of insider traders in a working from home (WFH) setting imposed by the Covid-19 pandemic. In our analysis we employ the aid of a methodology developed by (Cohen et al., 2012). The practice is based on the notion that insiders that exhibit more routine-like behaviour hold less of the informative power in the insider universe. By definition this implies that the non-routine insiders, whoms trading patterns are more sporadic, function as a stronger predictor of information related to the future of a firm. This is taken into account in our comparative analysis of the insider trades during the period leading up to Covid-19, contra the trades that take place in the midst of the pandemic. We firstly look into the differences that are visible in the performance of the opposing groups.

We find that there is indeed a large discrepancy in abnormal returns in between the group of trades that are conducted within the WFH period, when compared to the trades placed during the years prior to the outbreak. This is true when controlling for both non-routine and routine insider trades. In our baseline regression, the WFH variable yields additive abnormal returns of 129 and 131 basis points, depending on which industry is controlled for. In observing this contrasting effect, we showcase evidence that insiders perform significantly better under the conditions set by WFH. In addition to this, we find similar results to that of (Cohen et al., 2012) regarding the performance of routine versus non-routine trades. Namely, that non-routine trades generally outperform routine ones. However, our data indicates that both non-routine and routine trades are impacted positively in a WFH setting. In fact, routine trades experience a larger increase in abnormal returns during the WFH period, especially so when looking at returns from holding their respective position for 30 days. This reaction implies that non-routine traders are not the primary beneficiaries under the conditions that WFH generates, but rather that routine traders are equally, if not more, benefited by the surrounding circumstances.

To further complement our study, we look for the sector specific disparities. This analysis shows that the most notable industries exhibited similar results, namely that WFH trades outperforms No-WFH trades in terms of abnormal returns. This was true for, but not limited to, the Industrial, IT and Financial sector. Lastly we look at the changes in frequency of insider trades throughout the researched period. In this analysis we also demonstrate that insider frequency is observably higher during the years affected by Covid-19. Nevertheless, the scope of this paper and the rather small size in difference are not significant enough to make any conclusive insights.

The findings drawn from this study could potentially have value for both retail investors and financial supervisory authorities alike, with regard to the changes in insider behaviour during a period like the one induced by the Covid-19 pandemic and the consequent WFH setting that followed with it. It should however be noted that the Covid-19 crisis is rather unique in nature, and as a consequence it might prove difficult to encounter a similar event of the same magnitude.

6. References

Published papers:

Bettis, Carr, Vickrey, Donn, and Vickrey, Donn W, 1997, Mimickers of corporate insiders who make large-volume trades, Financial Analysts Journal 53, 57-66.

Bettis, J. C., Coles, J. L., and Lemmon, M. L., 2000, Corporate policies restricting trading by insiders, Journal of Financial Economics 57, 191-220.

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

Cohen, Lauren, Malloy, Christopher, and Pomorki, Lukasz, 2012, Decoding inside information, The Journal of Finance 67, 1009-1043.

Drobetz, Wolfgang, Mussbach, Emil, and Westheide, Christian, 2020, Corporate insider trading and return skewness, Journal of Corporate Finance 60, 101485.

Huddart, Steven J., and Ke, Bin, 2007, Information asymmetry and cross-sectional variation in insider trading, Contemporary Accounting Research 24, 195-232.

Jeng, Leslie A., Metrick, Andrew, and Zeckhauser, Richard, 2002, Estimating the returns to insider trading: A performance-evaluation perspective, Review of Economics and Statistics 85, 453-471.

Jenter, Dirk, 2005, Market timing and managerial portfolio decisions, The Journal of Finance 60, 1903-1949.

Kahle, Kathleen M, 2000, Insider trading and the long-run performance of new security issues, Journal of Corporate Finance 6, 25-53.

Kallunki, Jenni, Kallunki, Juha-Pekka, Nilsson, Henrik, and Puhakka, Mikko, 2018, Do an insider's wealth and income matter in the decision to engage in insider trading?, Journal of Financial Economics 130, 135-165.

Ke, Bin, Huddart, Steven, and Petroni, Kathy, 2003, What insiders know about future earnings and how they use it: Evidence from insider trades, Journal of Accounting and Economics 35, 315-346.

Knewtson, Heather S., Sias, Richard W., and Whidbee, David A, 2010, Style timing with insiders, Financial Analysts Journal 66, 46-66.

Lakonishok, Josef, and Lee, Inmoo, 2001, Are insider trades informative?, The Review of Financial Studies 14, 79-111.

Marin, Jose M., and Olivier, Jacques, 2008, The dog that did not bark: insider trading and crashes, The Journal of Finance 63, 2429-2476.

Tavakoli, Manouchehr, McMillan, David, and McKnight, Philip J, 2012, Insider trading and stock prices, International Review of Economics & Finance 22, 254-266.

Other sources:

EU's Market Abuse Regulation, Article 3.1.25. Palma, Stefania, Franklin, Joshua, 2021, JPMorgan to pay $200m over staff messages on personal devices, Financial Times, December 17.

FICC Markets Standards Board Annual Report, 2017. https://fmsb.com/wp-content/uploads/2017/09/FMSB_Annual_Report_Final_v2.pdf

Statistics Sweden (SCB), 2021-09-28, Ny statistik: Så många har jobbat hemifrån under pandemin. https://www.scb.se/pressmeddelande/ny-statistik-sa-manga-har-jobbat-hemifran-under-pandemin/

Swedish Financial Supervisory Authority Database, data from June 2016 to December 2021 https://marknadssok.fi.se/Publiceringsklient/en-GB/Search/Start/Insyn

7. Appendix

Appendix I

GICS Sector Codes and Included Industries

We use the GICS Sector Codes when performing our cross-industry analysis. The codes are developed developed by S&P Dow Jones Indices and MSCI. Below we see the different sectors used to identify in our dataset and the different industry groups that are included in it.

Sector	Industry Groups Included
Energy	Energy
Materials	Materials
Industrials	Capital Goods Commercial & Professional Services Transportation
Consumer Discretionary	Automobiles & Components Consumer Durables & Apparel Media Retailing
Consumer Staples	Food & Staples Retailing Food, Bevreges & Tobacco Household & Personal Products
Healthcare	Health Care Equipment & Services Pharmaceuticals, Biotechnology & Life Science
Financials	Banks Diversified Financials Insurance
Information Technology	Software & Services Technology Hardware & Equipment Semiconductors & Semiconductor Equipment
Telicommunication Services	Telecommunication Services
Utilities	Utilities
Real Estate	Real Estate

Appendix II
SCB Statistics on Industry WFH Rates

Based on data collected by Statistics Sweden (SCB) on industry specific statistics of how many were working from home in Sweden during the pandemic. Reported as percentages of the working population.

Industry Sector	Q3 2020	Q4 2020	Q1 2021	Q2 2021	Average
Agriculture. forestry and fishing	31.70%	31.40%	29.70%	31.20%	31.00%
Manufacturing and extraction. energy and environment	21.70%	28.60%	35.30%	32.80%	29.60%
Manufacture of engineering goods	25.70%	33.60%	39.00%	38.70%	34.25%
Construction activities	14.30%	20.40%	21.30%	18.80%	18.70%
Trade	24.50%	28.90%	30.80%	30.50%	28.68%
Transport	11.50%	16.00%	16.50%	15.70%	14.93%
Hotel and restaurant	6.70%	10.00%	6.80%	8.40%	7.98%
Information and communication	77.30%	83.50%	86.90%	83.60%	82.83%
Financial activities. business services	47.80%	56.80%	61.40%	59.60%	56.40%
Public administration, etc.	44.10%	59.20%	70.90%	67.10%	60.33%
Education	28.40%	35.40%	45.90%	40.80%	37.63%
Health and social care	9.20%	13.90%	16.50%	16.20%	13.95%
Personal and cultural services	31.70%	40.40%	44.90%	44.40%	40.35%