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Insider trading in a macroeconomic crisis

Evidence from the Finnish stock market during COVID-19 pandemic

Master's thesis
in Accounting and Finance

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COVID-19 pandemic had a significant impact on the global stock markets. The spreading of the virus launched a global stock market crash in the beginning of 2020, which was followed by a swift recovery in stock prices during the rest of the year. The market uncertainty level remained elevated after the crash at least until the first quarter of 2021. At the same time, corporate insiders are believed to be the most informed investors in the market. By examining the changes in their trading patterns and trading profitability during the crisis, a better understanding of the reasons and effects of the market turbulence can be achieved.

The purpose of the study is to analyse the effects of COVID-19 pandemic to insider trading in the Finnish stock market. The specific focus areas are the stock market crash of 2020 and the effect of COVID-19 related uncertainty on the short-term profitability of insider trading. The insider trading sample used in the thesis is limited to the companies listed in the main list of Nasdaq Helsinki during the three-year sample period from 2019 to 2021. Previous research has found that insider trading during stock market crashes can be indicative of the post-crash returns of the companies. Moreover, macroeconomic crises have previously found to have an impact on the short-term profitability of insider trading.

The results of the thesis show that the number of insider purchases peaked during the market crash of 2020, which indicates that insiders perceived the crash as a lucrative opportunity to increase the ownership stakes in their companies. However, other insider trading measures did not show similar significant changes during the crash. The changes in the insider trading during the crash are also indicative of the 6-month post-crash returns, although these results suffer from robustness issues caused by small sample size and multicollinearity. The results are inconclusive on whether the primary motive for insider trading during the crash was financial gain or signalling.

Regarding the short-term profitability of insider trading, only insider sales are followed with significant abnormal returns during the sample period. On the other hand, the COVID-19 related uncertainty affects only the profitability of insider purchases as abnormal returns following acquisitions are significantly lower during the crisis. This is due to the highly significant and negative returns after purchases during the market crash of 2020. The results imply that COVID-19 did not increase the information advantage of the insiders at least when measured with relatively short 21-day event windows. Lastly, trades by CEOs and CFOs appear to be more profitable in the short-term compared to other insider groups depending on details of the regression models used. The results also suggest that the profitability differences between insiders might be affected by macroeconomic crises.

Key words: Insider trading, COVID-19, coronavirus, pandemic, macroeconomic crisis, insider trading profitability, information asymmetry, signalling.

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Koronaviruspandemia vaikutti merkittävästi maailman osakemarkkinoihin. Viruksen leviäminen käynnisti vuoden 2020 alussa maailmanlaajuisen pörssiromahduksen, jota seurasi osakekurssien nopea elpyminen loppuvuoden aikana. Markkinoilla koettu epävarmuus pysyi romahduksen jälkeen kohonneella tasolla ainakin vuoden 2021 ensimmäiselle kvartaalille saakka. Toisaalta yrityksen sisäpiiriin kuuluvien henkilöiden uskotaan olevan markkinoiden parhaiten informoituja sijoittajia. Tarkastelemalla kriisin aikana tapahtuneita muutoksia sisäpiirin kaupankäynnissä ja sen kannattavuudessa voidaan ymmärtää paremmin markkinoiden epävakauden syitä ja seurauksia.

Tutkimuksen tavoitteena on analysoida COVID-19-pandemian vaikutuksia sisäpiirikaupankäyntiin Suomen osakemarkkinoilla. Tutkimuksen painopistealueina ovat vuoden 2020 pörssiromahdus ja koronaviruspandemiaan liittyvän epävarmuuden vaikutus sisäpiirikaupan lyhyen aikavälin kannattavuuteen. Tutkielmassa käytettävä sisäpiirikauppojen otos on rajattu koskemaan Nasdaq Helsingin päälistalla noteerattuja yhtiöitä kolmen vuoden tutkimusperiodin aikana 2019–2021. Aiemmissa tutkimuksissa on havaittu, että sisäpiirikauppa pörssiromahdusten aikana ennakoi yhtiöiden romahduksen jälkeisiä tuottoja. Lisäksi makrotaloudellisten kriisien on aiemmin havaittu vaikuttavan sisäpiirikaupan lyhyen aikavälin kannattavuuteen.

Tutkielman tulokset osoittavat, että sisäpiirin tekemien osakeostojen määrä oli korkeimmillaan vuoden 2020 markkinaromahduksen aikana, mikä viittaa siihen, että sisäpiiriläiset pitivät romahdusta hyvänä ostopaikkana. Muut sisäpiirikaupan aktiivisuutta kuvaavat muuttujat eivät kuitenkaan osoittaneet samanlaisia tilastollisesti merkitseviä muutoksia romahduksen aikana. Muutokset sisäpiirikaupankäynnissä romahduksen aikana ennakoivat myös romahduksen jälkeisiä kuuden kuukauden tuottoja, vaikka näiden tulosten luotettavuus kärsiikin pienestä otoskoosta ja multikollineaarisuudesta. Tulokset eivät ole yksiselitteisiä sen suhteen, oliko sisäpiirikaupan ensisijainen motiivi kriisin aikana taloudellisen hyödyn tavoittelu vai signalointi.

Sisäpiirikaupan lyhyen aikavälin kannattavuuden osalta voidaan todeta, että ainoastaan sisäpiirin myynneistä seuraa tilastollisesti merkitseviä epänormaaleja tuottoja tutkimusperiodin aikana. Koronavirukseen liittyvä epävarmuus sen sijaan vaikuttaa ainoastaan sisäpiirin ostojen kannattavuuteen, sillä ostojen jälkeiset epänormaalit tuotot ovat kriisin aikana tilastollisesti merkitsevästi pienempiä. Tämä johtuu vuoden 2020 markkinaromahduksen aikaisten osakeostojen erittäin merkitsevistä negatiivisista tuotoista. Tulokset osoittavat, että koronaviruspandemia ei lisännyt sisäpiiriläisten informaatioetua markkinoilla ainakaan, jos kannattavuutta mitataan suhteellisen lyhyillä 21 päivän tapahtumaikkunoilla. Lisäksi toimitusjohtajien ja talousjohtajien tekemät kaupat näyttävät olevan lyhyellä aikavälillä kannattavampia kuin muiden sisäpiiriläisten tekemät kaupat riippuen hieman käytettyjen regressiomallien yksityiskohdista. Tulokset antavat myös viitteitä siitä, että makrotaloudelliset kriisit saattavat vaikuttaa sisäpiiriläisten välisiin kannattavuuseroihin.

Avainsanat: Sisäpiirikaupankäynti, COVID-19, koronavirus, pandemia, makroekonominen kriisi, sisäpiirikaupankäynnin kannattavuus, epäsymmetrinen informaatio, signalointi.

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1 Introduction

1.1 Background

On March 26, 2020, Finnish business newspaper Kauppalehti published an article on insider trades in Nasdaq Helsinki between 24/2/2020 and 24/3/2020. The online article presented the stocks that had been bought the most by corporate insiders in total net value during the period. On the top of the list were stocks of companies such as Metsä Board Oyj, Kone Oyj and Fiskars Oyj. (Kauppalehti 26.3.2020.)

There is nothing special in writing about insider trades. Business newspapers report and analyse stock market transactions of corporate insiders on a regular basis (see e.g., Kauppalehti 24.9.2023; Talouselämä 27.9.2023; Niskakangas – Koistinen 2023). However, in March 2020 there was exceptional turbulence in the global stock markets. Due to the spreading coronavirus, stock prices were on a steep fall all over the world. For example, on March 16 the S&P 500 fell 12 percent, which was the worst day for the US equity market index since the crash of October 1987 (Financial Times 16.3.2020). Similarly, the cumulative drop of Nasdaq Helsinki was 28.12 percent between 24/2/2020 and 24/3/2020, which was the period covered in the insider trading article by Kauppalehti (Suomen Pankki 2023).

Almost 30 percent fall in the stock market indicates that the insider transactions listed in the article were not made under typical market conditions. However, the article emphasizes that insider trades might be especially interesting for investors when stock prices are falling. This view is based on the following rationale. Because there is so much uncertainty in the market, it is difficult to value stocks with normal valuation metrics. Therefore, it’s beneficial to look at the trades of top management, who can better evaluate the effects of the crisis on their business. (Kauppalehti 26.3.2020.)

But is there any truth in that argument? Are insiders capable of identifying and buying well performing stocks on a discount when other investors are panicking? Or was stock market crash of 2020 justified by radical changes in the underlying fundamentals? These are questions that this thesis is trying to answer.

Stock market crashes have been studied widely in academic literature, but corporate insider perspective is more uncommon. Seyhun (1990, 1386–1387) studied insiders’ aggregate response to the market crash of October 1987 and made several findings. Based on various measures of insider trading activity, he found that corporate insiders didn't foresee the crash of 1987. On the other hand, after the crash insiders bought stocks in record numbers, which indicates that insiders viewed the steep fall of prices as an overreaction. Most eager to buy their companies' stocks were top executives who are expected to be most knowledgeable of their business.

In addition, Seyhun (1990, 1386–1387) reported that the more the stock price had declined during the crash the more insiders bought it. Also, the stocks that were bought the most by insiders in October 1987 showed better returns in 1988 compared to other stocks. Seyhun's results suggest that insiders might be able to purchase undervalued stocks during stock market crashes.

But can individual insiders benefit from their position also when the market is not crashing? Shouldn't they have superior knowledge about their company all the time? Previous research has shown that insiders are able to accumulate abnormal returns in the stock market when trading with their companies' shares (see e.g., Lorie – Niederhoffer 1968; Jaffe 1974; Seyhun 1986; Lakonishok – Lee 2001). The results suggest that insiders seem to have an informational edge over other investors. However, an especially interesting question that this thesis focuses on is what happens to the informational advantage when unexpected events, such as a global pandemic, occur.

Although Finnish stock market reached its lowest point during the 2020 market crash already on March 18, 2020, the pandemic was far from over (Suomen Pankki 2023). The Finnish Government introduced a series of restrictions for people and companies during the March and April of 2020 to prevent the virus from spreading (see e.g., Valtioneuvosto 16.3.2020; Valtioneuvoston kanslia 28.3.2020; Valtioneuvoston kanslia 3.4.2020). It's reasonable to say that uncertainty created by the spreading coronavirus was still present in the society after the crash.

The unprecedented implications of a global pandemic were also a concern to market regulators. Due to the information asymmetry between insiders and outsiders, market regulators have introduced insider trading regulation to minimize insiders' advantage. Under the European Union's Market Abuse Regulation, public companies in Finland are required to disclose all information that is likely to have a significant impact on the stock price (Finanssivalvonta – Sisäpiiritiedon julkistaminen ja julkistamisen lykkääminen

2021). On March 11, The European Securities and Markets Authority (ESMA 11.3.2020) published the following statement.

> Issuers should disclose as soon as possible any relevant significant information concerning the impacts of COVID-19 on their fundamentals, prospects or financial situation in accordance with their transparency obligations under the Market Abuse Regulation.

The statement indicates that regulators were concerned about addressing the informational needs of outside investors.

Previous research on insider trading profitability during macroeconomic uncertainty is scarce. Van Geyt et al. (2013, 380–381) studied insider trading in the Belgian stock market during the financial crisis. They found that insiders earned significantly higher abnormal returns during the crisis compared to the non-crisis period. This implies that the higher level of uncertainty in the markets could be beneficial to insiders.

The results by Seyhun (1990) and Van Geyt et al. (2013) suggest that macroeconomic crisis, such as COVID-19, might have interesting implications on insider trading and its profitability. This thesis combines the perspectives of the two studies to gain a comprehensive understanding of those implications on the Finnish stock market. Insider trading data should provide insights into whether insiders believed that the stock market's reaction and the real-world effects of the crisis on the business were aligned.

The results of the thesis should be useful at least to investors and regulators. If insiders' information advantage in the markets is affected by a global pandemic, outside investors should re-evaluate the signal value of insider trades during crises. Moreover, if insiders are able to gain greater abnormal returns during crisis, it might indicate that the insider trading regulation is inefficient during market turbulence. The results of the thesis are also indicative of the efficiency level of the Finnish stock market.

1.2 Research objectives and research questions

The objective of the thesis is to understand the effects of COVID-19 pandemic to insider trading in the Finnish stock market. The specific focus areas are insider trading around the COVID-19 related stock market crash of 2020 and the profitability of insider trading under the uncertainty produced by the pandemic. Based on these perspectives three research questions are formed.

1. How did corporate insiders respond to the stock market crash of 2020?
2. What was the post-crash performance of the stocks that insiders traded during the market crash?
3. How did the COVID-19 pandemic affect the profitability of insider trading?

The first question addresses the perspective of stock market crash. It focuses on insiders' trading behaviour before, during and after the crash. The results should indicate whether insiders anticipated the crash and provide insights into their views on whether the crash was justified by a sudden change in fundamentals or potentially a sign of overreaction in the markets.

The second question combines the perspectives of market crash and trading profitability. It examines insiders' ability to identify potentially undervalued stocks during the crash by looking at the post-crash returns. If insiders were able to identify stocks that would overperform after the crash, it might indicate that markets overreacted to COVID-19 and insiders realized this.

The third question focuses on pandemic's effects on insider trading profitability. The idea is to examine, whether the uncertainty brought by a pandemic increases the possible information advantage of insiders. In contrast to the second research question, profitability is studied throughout the whole crisis using shorter time periods and abnormal returns.

1.3 Scope and limitations of the thesis

The thesis focuses on analysing insider trading during the COVID-19 pandemic in the Finnish stock market. Previous research on insider trading during macroeconomic crises is scarce, especially when both the aggregate insider trading approach and event study methodology are applied. According to a thorough research, there are no such studies done at least with Finnish data and focusing only on the effects of COVID-19. Therefore, there is a gap in the academic literature.

When it comes to the scope of thesis, the two most important questions are, which companies to include in the study, and what time periods to use in the study. Starting with the first question, the sample of companies examined in the thesis is limited to firms listed in the main list of Nasdaq Helsinki during the whole examination period. This period spans from the beginning of 2019 to the end of 2021.

Regarding the second question, there are limitations in the availability of data. The first transactions in the electronic database of Finanssivalvonta, which was acquired in the August of 2023, are from the beginning of 2019. This is due to a restriction stating that personal data must not be stored over 5 years under Article 28 of Market Abuse Regulation (Regulation 596/2014). Thus, the sample period starts from the beginning of 2019.

Based on World Health Organization's (WHO) information, the first reports of pneumonia cases in Wuhan, China came in on 31 December 2019. However, it was not until 11 March 2020, when COVID-19 was characterized as pandemic by WHO. (WHO 27.4.2020.) In addition, the global stock market crash of occurred in March 2020 (Kauppalehti 12.3.2020). This indicates that the crisis started during the first quarter of 2020 and is covered by the sample period.

The end of the COVID-19 crisis is more difficult to determine. The virus is still present in 2024, although WHO no longer defines the pandemic as a public health emergency of international concern (PHEIC) after 5 May 2023 (WHO 5.5.2023). Also, another major international crisis broke out in the spring of 2022, when Russia attacked Ukraine and Russo-Ukrainian war started (Helsingin Sanomat 24.2.2022). The negative effects of the war were seen in European stock markets, and especially in Russia's neighbouring country Finland (Helsingin Sanomat 4.3.2022). Therefore, the stock price movements from 2022 onwards are not regarded relevant for the purposes of this study, and the total sample period covers three years from 2019 to 2021. The specific time frames for the crisis period and the crash period used in the empirical analysis are developed and presented in section 5.

1.4 Structure of the thesis

The structure of the thesis consists of theoretical part and the empirical part. Chapters 2, 3, and 4 form the theoretical part of the thesis, and chapters, 5 and 6 are the empirical part. In addition, chapter 7 contains the conclusions of the thesis.

The theoretical part of the thesis is structured in a following manner. Chapter 2 defines insider trading, presents relevant parts of insider trading regulation, and introduces previous research results on insider trading profitability and aggregate insider trading. Chapter 3 presents the relevant theories affecting the dynamics of insider and outsider investors. These include efficient market hypothesis, theory of asymmetric information, agency theory, and signalling theory. Chapter 4 discusses COVID-19 pandemic and its effects on the stock markets and market uncertainty levels. It also presents previous research on the effects of macroeconomic crises to insider trading. The empirical part of thesis begins with chapter 5, which introduces the data, the methodologies, and the robustness checks used in the study. Chapter 6 presents and discusses the results.

2 Insider trading

This chapter defines insider trading, presents relevant parts of insider trading regulation, and introduces previous research results on insider trading profitability and aggregate insider trading.

2.1 Defining insider trading

Insider trading refers to stock transactions executed by a company's officers, directors, and significant shareholders. The interest in insider’s trades is based on a commonly held belief among investors that corporate insiders possess superior knowledge about their company's prospects, and they use this knowledge to buy and sell their company's stock at the most advantageous times. The demand for insider trading information is demonstrated in frequent articles about the topic in the financial press. (Seyhun 1998, 19–21.)

Insider trading is regulated in most countries. Bhattacharya and Daouk (2002, 104) report that over 80% of the countries which have stock markets have introduced insider trading laws. However, the common misconception that all profitable insider trading is illegal is not correct. Instead, insiders are prohibited to trade while possessing important information that is not available to the public (Seyhun 1998, 26–29). This raises the question whether insiders have any advantage in the market.

Seyhun (1998, 30–31) presents an example of a situation where insiders have a clear advantage but still don’t violate any insider trading rules. In a situation where company’s stock price drops significantly, and insiders don’t see any justification for this, they can purchase shares from the stock market. They are not acting on an important non-public information, as the price decline is public information. However, they are able to use their understanding of the business to evaluate the reasons behind the drop. As insiders seem to find ways to leverage their information advantage for personal gain even under regulation, it’s reasonable to ask why insider trading isn’t prohibited in the first place.

The debate on whether insider trading should be regulated or not has been going on for decades. Critics of the regulation argue that restricting insiders' trading activities leads to share prices that do not accurately reflect the true value of the companies. In other words, companies are not efficiently priced in the stock market without the involvement of insiders. (Aktas et al. 2008, 1379–1380.) The concept of efficient markets is introduced in detail in section 3.1. For example, Aktas et al. (2008, 1391) state, that insiders play a significant role in accelerating price discovery. Conversely, Fishman and Hagerty (1992, 106) argue that under certain circumstances, insider trading can lead to less effective pricing as it discourages other investors from obtaining information.

Supporters of insider trading regulation argue that controlling the information asymmetry between insiders and outsiders preserves market integrity by encouraging outsiders to participate in the markets and promoting the public confidence (Aktas et al. 2008, 1380). For example, Huddart et al. (2001, 665) argue that regulatory goals of publicly disclosing insider trades are to reduce this asymmetry. In the end, it seems that insider trading regulation is trying to find the right balance between market efficiency and market integrity.

2.2 Market abuse regulation

Insider trading regulation in Finnish stock market is based on European Union's Market Abuse Regulation (MAR), which became largely applicable on July 3, 2016. The central objective of the regulation is to ensure the integrity of financial markets and enhance investor protection. From the perspective of MAR, market abuse refers to activities such as insider dealing, unlawful disclosure of inside information and market manipulation. (Finanssivalvonta – Markkinoiden väärinkäyttöasetus 2018.) In this thesis, insider trading refers to the trading activities of individuals obligated to publicly disclose their trades under MAR.

2.2.1 Inside information, insider dealing, and insider lists

Article 7, point 1a of MAR (Regulation 596/2014) defines inside information as follows.

> Information of a precise nature, which has not been made public, relating, directly or indirectly, to one or more issuers or to one or more financial instruments, and which, if it were made public, would be likely to have a significant effect on the prices of those financial instruments or on the price of related derivative financial instruments.

This definition clarifies that not all non-public information is considered inside information as it must be "information of a precise nature" which is "likely to have significant effect" on stock price if published. However, neither of these terms is exact, which means that interpretation is needed. Point 2 and point 4 of Article 7 define the terms even further (Regulation 596/2014).

Information is regarded as precise in nature, if it refers to circumstances or events that have already occurred, or that can reasonably be expected to occur. In addition, these circumstances or events must be specific enough to draw conclusions about the potential impact of the information on the value of the financial instrument. Regarding the likelihood of information having a significant effect on stock price, the information must be such that a “reasonable investor” would consider it in their investment decision-making. (Regulation 596/2014.)

With the term inside information properly defined, the prohibitions laid out by MAR can be presented. Article 14 of MAR (Regulation 596/2014) contains the following prohibitions.

> A person shall not engage or attempt to engage in insider dealing, recommend that another person engage in insider dealing or induce another person to engage in insider dealing, or unlawfully disclose inside information.

Insider dealing, which is determined in MAR Article 8, occurs when an individual possesses inside information and utilizes that information to buy or sell financial instruments directly or indirectly, either for themselves or on behalf of a third party. Unlawful disclosure of inside information, discussed in MAR Article 10, arises when an individual, in possession of such information, reveals it to any other person, except in cases where the disclosure is part of their regular employment, profession, or duties. (Regulation 596/2014.)

In addition to prohibitions regarding utilization of inside information, issuers are also required to maintain a list of all persons, who have access to such information under MAR Article 18. This insider list must be kept updated and it must be provided to competent authority immediately when requested. Issuers are also required to ensure that insiders understand the sanctions associated with insider trading and the unauthorized disclosure of confidential information. (Regulation 596/2014.)

To conclude, MAR states that people who are in possession of important information that is not public and would affect stock price significantly if published are not allowed to use that information for their personal gain or share it with others. Moreover, persons who have access to such information must be listed into insiders list, which must be provided to competent authority upon request.

2.2.2 Disclosure requirements and trading restrictions

Disclosure requirements are another important part of MAR. Firstly, MAR Article 17 states that issuers are required to publicly disclose inside information directly related to them without a delay. Issuer can postpone disclosure on its own responsibility only if immediate disclosure is expected to harm its valid interests, withholding disclosure is unlikely to “mislead the public”, and the issuer can guarantee the confidentiality of the information. (Regulation 596/2014.)

Secondly, under Article 19 of MAR “persons discharging managerial responsibilities” and “persons closely associated with them” are required to notify the issuer and the competent authority concerning every transaction carried out for their own account involving shares or debt instruments of that issuer or related derivatives and financial instruments. The requirement is applicable to any subsequent transaction once the total sum of EUR 5,000 is achieved within a calendar year. The notifications must be submitted within a maximum of three business days from the transaction date and the issuer must disclose the transaction as soon as possible in a fast and non-discriminatory manner. The contents of a notification are defined in Article 19, point 6 of MAR. (Regulation 596/2014.)

Person discharging managerial responsibilities is defined in Article 3, point 25 of MAR as “a member of the administrative, management or supervisory body” of the company, or a senior executive, who has “regular access to inside information”, and “power take managerial decisions affecting the future developments and business prospects” of the company. (Regulation 596/2014.)

Person closely associated, defined in Article 3 point 26, refers to a spouse or a partner, a dependent child, or a family member living in the same household for a minimum of one year on the date of the transaction. Closely associated person can also be a legal person, trust, or a partnership, which is under the direct or indirect control of person discharging managerial responsibilities or person closely associated, established for their benefit, or with economic interests that align with those of such an individual. (Regulation 596/2014.)

There are also trading restrictions for persons discharging managerial responsibilities. Article 19, point 11 of MAR (Regulation 596/2014) addresses these restrictions.

> A person discharging managerial responsibilities within an issuer shall not conduct any transactions on its own account or for the account of a third party, directly or indirectly, relating to the shares or debt instruments of the issuer or to derivatives or other financial instruments linked to them during a closed period of 30 calendar days before the announcement of an interim financial report or a year-end report which the issuer is obliged to make public.

The disclosure requirements of MAR can be summarized as the obligation to promptly publish inside information, and the requirement for a firm's management and individuals closely associated with them to disclose their stock transactions involving their own companies' shares within three business days. Management is also prohibited from trading their own company's shares during the 30-day closed period before publishing financial reports.

2.2.3 Competent authority and legal consequences

Based on MAR Article 22, each Member State of EU must appoint an administrative competent authority for the implementation of MAR. (Regulation 596/2014.) In Finland, this competent authority is Finanssivalvonta. For example, notifications of management’s or closely associated person’s trades are submitted to an electronic system of Finanssivalvonta (Finanssivalvonta – Johtohenkilöiden liiketoimet ja suljettu ikkuna 2022).

Finanssivalvonta has published 10 guidelines for insider trading, which should be followed to avoid regulation violations. These instructions suggest avoiding active trading and recommend using written trading programs, where the terms regarding the quantity, price and trading times of transactions are clearly defined. The list also indicates that stock transactions are generally permissible for insiders regardless of insider information when they receive and exercise stock options as part of the management incentive program or when they receive shares as compensation. (Finanssivalvonta – Sisäpiiriläisen 10 kaupankäyntiohjetta 2018.)

Moreover, the list presents examples of other situations where trading is allowed even when possessing inside information. This could occur when an insider is buying (selling) stock, and the inside information they possess would have a clear negative (positive) impact on the stock price. Another example is a transaction that happens between two insiders, who both have the same piece of inside information. In this scenario, neither of the insiders can exploit the information advantage over the other. (Finanssivalvonta – Sisäpiiriläisen 10 kaupankäyntiohjetta 2018.)

When it comes to legal consequences of market abuse, the Criminal Code of Finland in chapter 51, defines the sentences. Abuse of inside information or unlawful disclosure of inside information leads to a fine or to imprisonment for up to two years. If the abuse of inside information is aggravated, for example when the profit is particularly great, the sentence is an imprisonment for at least four months and at most four years. (Criminal code 2021.) The length of the sentences indicates that market abuse is punished severely.

2.3 Previous research on insider trading

2.3.1 Insider trading profitability

The interest of investors in tracking insider trades and the regulatory focus on overseeing insider trading both stem from the shared belief that insiders utilize their informational advantage to make more informed investment decisions than others. To evaluate the accuracy of such belief, previous results on insider trading profitability are presented in Table 1. The research on the topic is extensive and thus only the most notable studies are considered in this thesis.

Table 1. Previous results on profitability of insider trading.

Research	Market	Sample	Method	Result
Lorie – Niederhoffer (1968)	US	1950–1960	Total return	Insiders get higher returns
Jaffe (1974)	US	1962–1968	Risk adjusted return (Market model)	Abnormal returns for insiders
Finnerty (1976)	US	1969–1972	Risk adjusted return (Jensen alfa)	Abnormal returns for insiders
Givoly – Palmon (1985)	US	1973–1975	Risk adjusted return (Market model)	Abnormal returns for insiders
Seyhun (1986)	US	1975–1981	Risk adjusted return (Market model)	Abnormal returns for insiders
Rozeff – Zaman (1988)	US	1973–1982	Risk adjusted return (Market model)	Abnormal returns for insiders
Brick et al. (1989)	US	1976–1979	Risk adjusted return (Multiple models)	Abnormal returns for insiders
Pope et al. (1990)	UK	1977–1984	Risk adjusted return (Multiple models)	Abnormal returns for insiders
Gregory et al. (1994)	UK	1984–1986	Risk adjusted return (Market model)	Abnormal returns for insiders
Bettis et al. (1997)	US	1985–1990	Risk adjusted return (Market model)	Abnormal returns for insiders and outsiders

Research	Market	Sample	Method	Result
Eckbo – Smith (1998)	Norway	1985–1992	Risk adjusted return (Multiple models)	No abnormal returns for insiders
Kasanen (1999)	Finland	1996–1997	Risk adjusted return (Multiple models)	No abnormal returns for insiders
Lakonishok – Lee (2001)	US	1975–1995	Risk adjusted return (Aggregate trading approach)	Insider purchases are informative
Del Brio et al. (2002)	Spain	1992–1996	Risk adjusted return (Multiple models)	Abnormal returns for insiders
Hillier – Marshall (2002)	UK	1991–1997	Risk adjusted return (Modified market model)	Abnormal returns for insiders
Friederich et al. (2002)	UK	1986–1994	Risk adjusted return (Market model)	Abnormal returns for insiders
Jeng et al. (2003)	US	1975–1996	Risk adjusted return (Multiple models, portfolio approach)	Abnormal returns for insiders in purchases
Fidrmuc et al. (2006)	UK	1991–1998	Risk adjusted return (Market model)	Abnormal returns for insiders
Betzer – Theissen (2009)	Germany	2002–2004	Risk adjusted return (Market model)	Abnormal returns for insiders
Gangopadhyay et al. (2009)	US	1999–2002	Risk adjusted return (Aggregate trading approach)	Abnormal returns for insiders
Jagolinzer et al. (2011)	US	2006–2007	Risk adjusted return (4-factor model)	Abnormal returns for insiders in purchases
Van Geyt et al. (2013)	Belgium	2006–2010	Risk adjusted return (Market model)	Abnormal returns for insiders
Gebka et al. (2017)	18 European countries	1999–2012	Risk adjusted return (Multiple models, portfolio approach)	No abnormal returns for insiders in most countries

The results presented in Table 1 indicate that insiders gain abnormal returns when trading with their company's stock. Vast majority of previous studies (see e.g., Jaffe 1974; Seyhun 1986; Jeng et al. 2003) have reported excess returns for insiders and only a few studies (see e.g., Eckbo – Smith 1998; Kasanen 1999; Gebka et al. 2017) have reached an opposite conclusion. The results seem to imply that insider trades contain valuable information for investors and that insider trading regulation hasn't been successful in limiting the returns of insiders. However, it's noteworthy that the only study from the Finnish stock market did not find evidence of excess returns.

A deeper analysis of the results reveals insights regarding differences between insider purchases and insider sales. According to a conventional wisdom, there are many reasons for an insider to sell their shares, but only one reason to buy, which is to make money. The results of Lakonishok and Lee (2001), Jeng et al. (2003) and Jagolinzer et al. (2011) support this view, as they found abnormal returns associated only with insider purchases. However, there are also some contrasting results on the issue, as reported by Del Brio et al. (2002, 82).

Another question that seems to divide researchers is whether outsiders, who mimic insiders' trades can earn abnormal returns. For example, Bettis et al. (1997) report that it is possible, while Seyhun (1986) argues that outsiders do not earn excess returns after adjusting for trading costs. Although the topic is out of the scope of this thesis, it should be noted that abnormal insider returns do not necessarily mean abnormal outsider returns. After all, the primary motivation for many investors to follow insider trades is to find money making opportunities.

Even though the results in Table 1 seem to be rather unanimous, reaching a definitive conclusion on insider trading profitability is complicated. Firstly, it should be noted that most of the research has been conducted using US data from the New York Stock Exchange (NYSE). Stock market dynamics might be different in other countries, which should be considered when generalising the results. Secondly, sample periods vary significantly between the studies, and general market conditions are not comparable in different decades. For example, in the 1950s the insider trading data of NYSE was published approximately five weeks after the last insider trade of the month in the Official Summary of Stock Transactions by The Securities and Exchange Commission (SEC) (Lorie – Niederhoffer 1968, 36). Currently, the insider trading information is collected electronically and published with a much shorter delay as described in section 2.2.

Thirdly, and most importantly, methodologies used in the research papers have a substantial impact on the results. The earliest study by Lorie and Niederhoffer (1968, 53) found that stocks, which are bought by insiders in large numbers are expected to earn higher returns than the market on average. Although this result suggests that insiders can outperform the market, it doesn't consider the level of risk involved. The bigger returns of insiders could simply be due to their willingness to take more risks than an average investor and not due to their superior information.

Therefore, almost all the subsequent studies have used some method for adjusting the returns for risk. To put it concisely, observed stock returns of insiders are compared to returns predicted by an appropriate asset pricing model which considers the risk level of the company. Higher risk companies should have higher expected returns and vice versa. The difference between the predicted return and the actual return is the abnormal return. Because the exact holding periods of insiders are difficult to determine, the performance of a trade is measured by calculating the abnormal returns from couple of days to many months after the transaction, depending on the study. This complicates the comparison of different studies and the magnitude of the abnormal returns reported in them.

Moreover, asset pricing models have a crucial role in the studies, because depending on the model used, the abnormal returns change. For example, Brick et al. (1989, 422) used four different models to calculate the abnormal returns and found that both the size of the returns and their statistical significance varied depending on the model. This leads to joint hypothesis problem, which is described in detail in section 3.1.2.

Overall, previous results indicate that insiders can earn abnormal returns. However, to evaluate the reliability of the results and the possible reasons for the returns, more information on the joint hypothesis problem and other theoretical background is needed. Section 3 discusses these themes in detail.

2.3.2 Aggregate insider trading

Most of the studies listed in Table 1 focus on the profitability of individual insider trades and use event study methodology. However, some studies, such as Lakonishok and Lee (2001) and Gangopadhyay et al. (2009), adopt an aggregate insider trading perspective. As this thesis uses both the profitability analysis and aggregate insider trading approach, some key studies regarding the latter are introduced.

Instead of focusing on individual trades, insider trades can be combined to aggregate insider trading data. This data can then be used to explain economywide phenomena as the data is no longer linked to individual firms. For example, Seyhun (1988, 22) found that net aggregate insider trading correlates positively with market portfolio return of the following two months. Insiders in total purchase shares before stock market rises and sell them before it drops. Seyhun (1988, 22) explains this by arguing, that although all insiders trade with the stock of their own company, the underlying reason to do so might be in some economywide factor that influences their company. This economywide factor also influences the returns of the market portfolio, and thus insiders together are able to predict movements of the market.

Lakonishok and Lee (2001, 82) reported similar findings to Seyhun (1988). They conclude that aggregate insider trading “could be used as a tool to time the market”. In addition, Seyhun (1992) found evidence of relation between aggregate insider trading and future real activity. Measures for real activity included after-tax profit growth rates, the Gross National Product, and the Index of Industrial Production. In addition, aggregate insider trading explains future stock returns even when the changes in real activity are considered, which indicates that predictive power of aggregate insider trading is not solely based on inside information about future activities.

Other examples of studies using aggregate insider trading approach include Rozeff and Zaman (1998) and Jiang and Zaman (2010). For the purposes of this thesis, aggregate insider trading approach is useful when studying the behavior of insiders during the stock market crash of 2020. Previous results concerning insider trading behavior around macroeconomic crises are introduced in section 4.2.

3 Theoretical background

This chapter presents the relevant theories affecting the dynamics of insider and outsider investors. These include efficient market hypothesis, theory of asymmetric information, agency theory and signalling theory.

3.1 Efficient market hypothesis

3.1.1 Defining efficient markets

Efficient markets are defined in Eugene Fama's classic finance article from 1970 as markets, where "security prices at any time fully reflect all available information". In such markets, the expected excess return of any trading system that utilizes information is zero, as all information is already included in the prices. (Fama 1970, 383–385.) According to the hypothesis, security prices only react to new information, and this reaction is immediate due to the fierce competition in the markets. Because new information cannot be predicted the future price changes of securities are also unpredictable. (Alvarez – Koskinen 2007, 40.)

It should be noted that the efficient market hypothesis does not claim that market prices accurately reflect information that is revealed in the future. For example, 2008 financial crisis revealed that the share prices of numerous banks and other firms were inflated in 2007. In hindsight, selling bank stocks in 2007 would have been a lucrative trading opportunity. However, this observation alone doesn't disprove market efficiency. To challenge the concept, one would have to demonstrate that the financial crisis was easily foreseeable in 2007 and that many investors profited from trading on that foresight. The limited number of such investors following the financial crisis underscores that predicting it was not evident at the time. (Berk – DeMarzo 2014, 469.)

The hypothesis that all available information is always fully reflected in the prices is an extreme null hypothesis. Fama (1970, 388) emphasizes that the hypothesis is not expected to be literally true, but rather a concept through which the level of information at which the hypothesis breaks down can be estimated. He suggests that this estimation can be done by dividing the efficiency tests into three categories based on the information used in them. These categories are weak form efficiency, semi-strong form efficiency and strong form efficiency.

If the markets are efficient in the weak form, the prices reflect all historical price information (Fama 1970, 388). In other words, future returns of a security can't be predicted using past returns. In addition to security returns, Fama (1991, 1576) suggested later that also return predictability tests using other variables such as dividend yields, or interest rates should be included in this category.

In markets that are efficient in semi-strong form, all publicly available information is reflected in the prices. Tests included in this category usually measure how quickly prices adjust to new information. (Fama 1970, 388.) In semi-strong form efficient markets, no strategy that is based on publicly available information should consistently gain excess returns for investors (Berk – DeMarzo 2014, 469).

In strong form efficient markets all information including inside information is reflected in the prices (Alvarez – Koskinen 2007, 40). This means that excess returns cannot be achieved even when holding information that is relevant for the stock price and not publicly available (Berk – DeMarzo 2014, 469). Tests included in this category examine whether any investor group has a monopolistic access to such relevant information (Fama 1970, 388). However, Fama (1970, 414) described strong form efficiency primarily as a benchmark for market efficiency rather than an exact description of the world.

The sufficient market conditions for efficient markets contain the the assumption of frictionless markets, where there are no trading costs, information is available for free, and all investors agree on the implications of given information (Fama 1970, 387). Originally, Fama (1970, 387–388) stated that this assumption is not a necessity for efficient markets, although market friction might be a source for inefficiency.

After Grossman and Stiglitz (1980, 404) argued that costless information is a necessary condition for market efficiency, Fama (1991, 1575) specified his views on the issue. He stated that the absence of information and trading costs is a precondition for strong form efficiency. Thus, the extreme version of the hypothesis can be rejected. However, the concept of extreme efficiency can still be used as a benchmark, and investors should decide for themselves, whether the deviations from the strong form efficiency are within the range of information and trading costs. (Fama 1991, 1575.)

3.1.2 Joint hypothesis problem

Before presenting the main results on market efficiency, a major issue concerning efficiency testing, joint-hypothesis problem, should be addressed. To examine whether prices fully reflect all available information, observed prices are compared to the predictions of an appropriate asset pricing model. Consequently, the efficient market hypothesis cannot be tested separately from the asset pricing model. (Fama 1991, 1575–1576.)

The joint-hypothesis problem causes difficulties when analysing results on market efficiency. The deviations between observed prices and predicted prices can stem from market inefficiency or a flawed asset pricing model, and it's difficult to determine their individual contributions accurately. Therefore, Fama (1991, 1575–1576) stated that "precise inferences about the degree of market efficiency are likely to remain impossible".

When testing for market efficiency, Berk and DeMarzo (2014, 458) offer two possible explanations for positive abnormal returns:

1. The asset pricing model used doesn't capture all the risks of a certain stock and therefore underestimates the risk premium that investors require to invest in that stock. Consequently, the realized returns of the stock exceed the predicted returns of such model.

2. The asset pricing model used captures all the risks of a certain stock, but for some reason investors systematically avoid the opportunity to earn extra returns without bearing any extra risk by not investing in the stock. This might be due to ignorance of the opportunity or because costs of the strategy are bigger than the returns.

These explanations suggest that the role of the asset pricing model is essential when testing for efficiency. The better the asset pricing model is at capturing risk, the better the reliability of the efficiency test results. If the first explanation is true and asset pricing model is unreliable, detected abnormal returns do not prove inefficiency of the markets. However, if the latter explanation is true, abnormal returns would be evidence against efficiency. Even then, the inefficiency of the markets doesn't necessarily give investors opportunities to make money.

To be precise, there is also a third explanation. The asset pricing model could be accurate, but abnormal returns may still emerge purely by chance. There's always the possibility that a specific sample is heavily skewed towards a pattern that isn't representative of the entire population. If this were the case, the abnormal returns wouldn't be evidence against efficiency, as the hypothesis only states that the expected excess returns are zero.

One way to reduce the joint-hypothesis problem in event studies, which are used to test semi-strong form efficiency, is to use daily returns. Fama (1991, 1601) argues that if the response to an event is very concentrated and big enough, it doesn’t matter which asset pricing model is used to predict the expected returns. The excepted daily returns are in all cases relatively close to zero. Although this might eliminate the joint hypothesis problem, event studies contain another problem, which is that there is no way of knowing what the true cause behind abnormal reaction is. It might be the event studied or some other event that happened at the same time.

3.1.3 Previous research on market efficiency

The debate over market efficiency has persisted for decades within academic literature. The early tests in 1960s and 1970s, which generally focused on short time periods, found results that were consistent with the efficient market hypothesis (Fox 2014). For example, Fama (1970, 414–415) argued that there is strong support for weak form efficiency and decent support for semi-strong efficiency. Regarding strong form efficiency he identified two groups who have monopolistic access to information. These were specialist in major security exchanges and corporate insiders.

However, after the early success of the hypothesis some contradictory results started to appear. Already in 1980, Grossman and Stiglitz (1980, 405) argued that the concept of efficient markets is impossible, because information is costly. In efficient markets nobody would have any incentive to acquire information, if they don’t gain any extra profits but must pay for it. In such market, the prices cannot reflect all information. The conflicting results combined with economists who used psychological and behavioral elements in stock price determination gave rise to behavioral finance, which questioned the original hypothesis (Malkiel 2003, 60). A couple of the key findings that challenge the hypothesis are return predictability and size and value effects.

Firstly, unlike weak form efficiency suggest, stock returns seem to be predictable. Jegadeesh and Titman (1993, 89) found that a strategy of buying past winners and selling past losers gained significant abnormal returns during six month holding period. This implies that short-term returns are positively autocorrelated. Moreover, De Bondt and Thaler (1985, 804) found negative autocorrelation in long term returns. In their study, the prior losers beat the prior winners during the 3-year holding period by around 25%, although winner stocks were riskier. Fama and French (1988, 247) also reported large negative autocorrelations for long term returns. In addition to autocorrelations, dividend yields seem to also predict stock returns (Fama 1991, 1583).

Although return predictability is clearly against the efficient market hypothesis, drawing definitive conclusions isn't simple. Both supporters and critics of the hypothesis proposed their own explanations for the phenomenon. Behavioral finance offered two explanations for short-term positive autocorrelations also called momentum. It can be a result of a bandwagon effect, where investors are interested in stocks that have performed well lately and dislike stocks with low recent returns. Alternatively, momentum might be caused by an underreaction to new information, which will be fully reflected in the stock price only after a period of time. (Malkiel 2003, 61.) When it comes to long term predictability, De Bondt and Thaler (1985, 804) argued that the negative autocorrelation is due to investors tendency to overreact to unexpected events.

Fama (1998, 284) pointed out that single pieces of evidence from investor underreaction and overreaction don't disprove market efficiency especially when there is no unified theory to explain them. A roughly even split between overreactions and underreactions is consistent with market efficiency as excepted excess returns should still be zero. Later, Daniel et al. (1998, 1841) developed a unified theory, which was based on investor overconfidence and self-attribution. They argued that these psychological factors trigger a loop of overreaction and correction, where prices are positively autocorrelated in short-term, but have negative autocorrelation in long term.

The explanation for predictability which is supportive to the efficient market hypothesis is that risk premium is not constant but changes rationally over time (Fama – French 1988, 247). Cochrane (2011, 1091) argues that the variability in discount rates exceeds our initial expectations and majority of the puzzles and anomalies stem from fluctuations in discount rates. In an earlier paper, he argued that excess returns are predictable (Cochrane 2008, 1572). John Campbell, a renowned economics professor at Harvard, explains in an interview by Harvard Business Review (Fox 2014), how long swings in risk premium could be explained without irrational beliefs.

> So in a time like the 1960s, when there's been a lot of growth, people are feeling rich and they're willing to take risks because they've got a cushion of comfort above their baseline expectation. At a time like the present when things have not been so great, people's standard of living is much closer to the baseline minimum that they expect, and they don't feel like they have a big cushion of comfort. That's a model in which people have reasonable expectations about the future, they just worry about risk a lot more in bad times than in good times.

Still, the issue of predictability remains debatable. As Fama (1991, 1581) argues "a ubiquitous problem in time-series tests of market efficiency, with no clear solution, is that irrational bubbles in stock prices are indistinguishable from rational time-varying expected returns".

Secondly, size effect and value effect have challenged the efficient market hypothesis. Banz (1981, 16) found that small firms have earned significantly higher risk-adjusted returns than large firms. Similarly, value stocks, which have low price-to-book values, have earned abnormal returns (Malkiel 2003, 69). As previously mentioned, asset pricing models play a crucial role in efficiency testing due to the joint-hypothesis problem. The Capital Asset Pricing Model (CAPM), which relies on a single risk factor (beta), has served as the model against which numerous irregularities have been identified (Fama, 1991, 1589).

CAPM is a simple and intuitive approach to pricing assets, but its empirical record isn't the best (Fama – French 2004, 25). Thus, the size effect and value effect aren't necessarily evidence against efficiency but might rather indicate that there is some risk involved with smaller firms and value firms, that CAPM doesn't capture. Based on this idea, Fama and French (1992, 427) created a three-factor model for asset pricing, where they added size factor and value factor to the model. Later, they added two more factors, profitability, and investment, to their updated five-factor model (Fama – French 2015, 1).

The three-factor model is better at explaining stock returns than CAPM and has thus been used as a benchmark in some efficiency tests. However, the comparison between the two models leans toward the three-factor model, as it has been constructed by identifying variables from data afterwards. Consequently, it is not surprising that it performs better. (Fama 1991, 1598.) The problem of three-factor model is that there seems to be no clear empirical motivation for size factor and value factor. It also can't explain momentum effect. (Fama – French 2004, 39–40.) In defense of CAPM it can also always be stated that the poor performance might be due to a bad proxy for market portfolio, which results in incorrect betas. In addition to return predictability and size and value factors, there are also other results that challenge market efficiency, such as seasonal anomalies and equity risk premium puzzle, but these aren't presented in this thesis (Malkiel 2003).

Despite the continuous debate, the prevailing perspective in the literature tends to support the notion that markets are reasonably efficient. Also, the ambiguous nature of the efficient market concept complicates the task of rejecting the hypothesis. (Alvarez and Koskinen 2007, 40.) Faulty asset pricing model, time varying risk premium, and data mining are all efficiency consistent explanations for inefficiencies. Data mining involves researchers exploring vast financial databases, leading to the discovery of seemingly significant yet ultimately incidental relationships between financial variables (Malkiel 2003, 72). To conclude, the efficient market hypothesis, as any model, is surely an imperfect representation of price formation, but replacing it with an alternative model that can be empirically rejected hasn't yet happened. (Fama 1998, 284.)

3.1.4 Strong form efficiency and insider trading

The most relevant results for the purposes of this study are the results on strong form efficiency. Insiders seem to be able to earn abnormal returns, which indicates that markets are not efficient for insiders (Fama 1991, 1603). The same conclusion can be drawn from the long list of research papers presented in Table 1 in section 2.3.1, as majority of them supports insiders' ability to earn abnormal returns. However, the issues caused by joint hypothesis problem and detected market anomalies are also present in insider trading studies. As previous research on market efficiency has found evidence of return predictability, size effect and value effect, these factors might partly explain the abnormal returns of insiders. Therefore, a further analysis of the insider trading profitability results is needed.

Starting with the return predictability, long-term negative autocorrelation of returns reported by De Bondt and Thaler (1985, 804) means that a simple contrarian investment strategy of buying past losers and selling past winners can be profitable. Some previous studies (see e.g. Rozeff and Zaman 1998; Lakonishok and Lee 2001; Jenter 2005) have found evidence that insiders apply contrarian strategy, which means that their abnormal returns might not be solely due to superior information about the company. The extent to which contrarian strategy explains insider returns remains debatable.

Lakonishok and Lee (2001, 81–82) argue that although insiders are contrarian investors, they are better at market timing than a simple contrarian investor. Piotroski and Roulstone (2005, 78) and Gangopadhyay et al. (2009, 60) found that contrarian strategy and superior information both contribute to insider returns. In contrast, Jiang and Zaman (2010, 1235) suggest that insiders returns are driven by insiders' ability to predict future cash flows.

When it comes to size and value effects, several studies such as Rozeff and Zaman (1998, 701), Lakonishok and Lee (2001, 109), Jeng et al. (2003, 467) and Gangopadhyay et al. (2009, 50) have reported that insiders tend to prefer small stocks and value stocks in their investing. As these stocks have outperformed the market in the past, insider trading profits are overestimated in studies that do not adjust for firm size and valuation ratios (Lakonishok – Lee 2001, 100).

Rozeff and Zaman (1988, 42–43) adjusted their abnormal returns for size and value effects and presented lower abnormal returns after the adjustment than when using normal market model. They argue that at least abnormal outsider returns disappear when adjusted returns and transaction costs are considered. Lakonishok and Lee (2001) and Jenter (2005) report similar findings in their studies. In addition, adjusting for only one of the anomalies can be enough to affect the returns. For example, Gregory et al. (1994, 52) found that a significant portion of insiders' abnormal returns occurred in small and medium-sized firms, and once they controlled for the size effect, the statistical significance of the results decreased. Moreover, some other studies listed in Table 1 in section 2.3.1, such as Bettis et al. (1997) and Hillier and Marshall (2002), which didn't focus specifically on anomalies, also adjusted their asset pricing models for firm size bias by assumption.

Overall, the results regarding the effects of market anomalies on insider trading returns challenge the reliability of studies that have not accounted for these effects. Therefore, relevant controls for the most common anomalies are considered in the empirical part of this thesis. Still, it can be concluded that insiders most likely earn some abnormal returns due to their superior information, and thus strong form efficiency doesn't hold. Although the use of inside information is prohibited by trading regulations, misconducts are always possible. In addition, insiders have legal ways to benefit from their superior knowledge (Seyhun 1998, 30–31). This thesis focuses on insider trading during COVID-19, but the results also contribute to the research on efficiency of the Finnish stock market. If corporate insiders gain abnormal returns with their superior knowledge, it indicates that there are some inefficiencies in markets.

3.2 Theory of asymmetric information

3.2.1 Adverse selection and moral hazard

Information asymmetry refers to a situation where some market participants have more information than others. Asymmetric information in the markets is perceived problematic because it causes two problems, adverse selection, and moral hazard. (Leach 2004, 293.) These problems can lead to suboptimal decision making, market inefficiencies or even break down the whole market.

The adverse selection problem is caused by hidden information that some market participants possess, whereas the moral hazard problem stems primarily from the hidden actions of certain participants (Darrough – Stoughton 1986, 501). When it comes to insider trading, both problems are present. Firstly, corporate insiders have access to internal information of the company and thus possess hidden information. Secondly, outsiders' capability to oversee management actions is limited, which might lead to hidden actions and moral hazard problems.

Akerlof (1970, 489) demonstrates the adverse selection problem arising from information asymmetry in his classic article from 1970. He presents with an example from car market how information asymmetry leads to market breakdown. In his example, there are only good cars and bad cars in the market. Sellers know the quality of their car, but buyers don't, which means that sellers have an informational advantage. Buyers price the cars in the market based on the probabilities of acquiring a good car or a bad car. The possibility of buying a bad car decreases the price of all cars, which means that sellers of good cars retrieve from the market. In the end, the information asymmetry and adverse selection problem destroys the whole market.

In the stock market, the adverse selection problem can be demonstrated through the actions of market-makers, who provide liquidity to the markets. They offer to buy and sell the same stock at the same time in hopes of profiting from the difference between the prices, called bid-ask spread. However, if there are informed traders, such as corporate insiders, in the market, the market-maker will consistently incur losses to informed traders. Market-maker buys stocks from informed traders before subsequent abnormal declines in stock prices and vice versa, which consequently means that the abnormal profits accrued by informed traders come at the market-maker's expense. (Seyhun 1986, 191.)

Because market-maker lacks the ability to differentiate between informed and uninformed traders before engaging in trades, they must charge all traders based on the anticipated value of their potential non-public information. In other words, market maker decreases their purchase prices and increases their ask prices for all market participants. Despite this adjustment leading to wider bid-ask spread, the market-maker continues to endure overall losses from trading with informed traders. However, these losses are counterbalanced by gains made from uninformed traders. The uninformed traders, unaware of the asymmetry in information, end up paying a higher bid-ask spread to trade with the market-maker, which has a negative effect on their profits. (Seyhun 1986, 191.)

Although information asymmetry causes losses to uninformed outsiders through adverse selection problem, Bhattacharya and Nicodano (2001, 1155) argue that insider trading might still be beneficial for the welfare of outsiders. They demonstrate how insider trading improves risk sharing between outsiders with their intertemporal model. The rationale behind the finding is that the positive influence of insider trading on the selling prices and consumption of outsiders in some circumstances outweighs the negative impact of adverse selection losses experienced in other situations.

The moral hazard problem arises when some participant can use hidden actions or sometimes also hidden information to affect the outcome of a contract (Leach 2004, 293). For example, a person who insures his car might start to drive more recklessly and take more risks in the traffic because there is no downside for him if an accident occurs. However, the insurance company is affected by the hidden actions of the insured, and ultimately greater risks taken will raise the car insurance payments of all customers. In the insider trading context, moral hazard problem can lead to suboptimal decision making. If insider trading is allowed, insiders are able to profit both from good news and bad news. In the worst-case scenario, a manager could short his company’s stock and then make bad business decision to decrease the stock price. (Padilla 2002, 5.) The relationship between owners and managers are described in detail in section 3.3, which introduces agency theory.

3.2.2 Sources of information asymmetry in insider trading

Several factors including company related factors, insider related factors and the level of investor protection affect the size of the information asymmetry between insiders and outsiders, and thus insider trading returns. Starting with the company related factors, size of the company seems to have some influence. Seyhun (1986, 210) found that the expected losses to insiders are bigger in smaller firms. This finding aligns with the earlier hypothesis, that the adverse selection problem is reflected in bid-ask spread, as smaller firms tend to have larger spreads. Similarly, Lakonishok and Lee (2001, 82) argue, that insider trades are more useful signals in small companies, because larger companies are priced more efficiently.

Fidrmuc et al. (2006, 2969) report that ownership structure of the firm influences insider returns. They argue that the price reaction to insider trades is greater if an institutional investor is a major owner of the company. On the other hand, firms where families or corporations have ownership, the reaction is limited. The rationale for this is, that families and corporations monitor their management more efficiently, which reduces the information advantage of insiders. In contrast, Betzer and Theissen (2009, 421) did not find evidence that the identity of the controlling shareholder matters. However, they found that price reactions are greater in widely held firms. In addition to size and ownership structure, for example Aboody and Lev (2000, 2747) found that insider gains, and thus information asymmetry, are greater in firms with higher R&D spending.

When it comes to insider related factors, the impact of insider's position remains debatable. The studies by Seyhun (1986, 210) and Lin and Howe (1990, 1283) both support information hierarchy hypothesis, which states that most knowledgeable insiders, such as chairmen of the board or CEOs, possess more valuable information to trade on than other insiders. Consequently, the information asymmetry between an outside investor and CEO is greater than with a member of lower-level management. However, Betzer and Theissen (2009, 427) and Fidrmuc et al. (2006, 2969) did not find support for information hierarchy hypothesis in their studies. Also, the hierarchy of the insiders isn't obvious as the results by Wang et al. (2012, 760–761), who found that CFO purchases are more informative than CEO purchases, show.

Lastly, the level of investor protection is linked to the size of the information asymmetry. Dai et al. (2016, 250) found that insider trading returns are lower in more effectively governed firms. Frankel et al. (2004, 255-256) found that analyst following reduces the insiders' profits and therefore information asymmetry. Piotroski and Roulstone (2005, 78) report similar findings. In contrast, Gebka et al. (2017, 86), who investigated profitability of insider trading in 18 European countries, found some evidence that higher investor protection is linked to higher insider returns after purchases. Their rationale for this is that insider trades might be viewed as more reliable signals in more controlled environments.

3.3 Agency theory

Agency theory focuses on describing and explaining an agency relationship between a principal and an agent. The agency relationship forms when the principal hires the agent to make decisions on his behalf. If both parties aim to maximize their utility in this relationship, it is possible that an agency problem arises as the agent may occasionally act against the best interests of the principal. To prevent such occurrences, the principal attempts to incentivise the agent appropriately. However, incentives and monitoring of the agent generates agency costs for the principal. The key question of agency theory is to determine how the principal can ensure that the agent is maximizing his utility. (Jensen and Meckling 1976, 308.)

There is a clear agency relationship between the management of a company and its shareholders (Jensen and Meckling 1976, 309). Eisenhardt (1989) presents two general approaches used by firms to solve the agency problem, which are behaviour-oriented contract and outcome-oriented contract. First one relies on monitoring the agent and revealing his hidden actions, while the latter attempts to align the goals of the principal and the agent. Eisenhardt (1988, 506) argues that companies prefer behaviour-oriented contracts and use outcome-oriented contracts only when behaviour of the agent is difficult to measure.

Insider trading can be viewed as a way to align the interest of shareholders and management. If insiders purchase the shares of their own company, their compensation is linked to the performance of the stock. Moreover, insiders can alter the contents of their compensation package by trading the stock. (Carlton – Fischel 1983, 870–871.) However, as has been discussed earlier, the management (insiders) is more informed about the business prospects than the shareholders (outsiders) and can therefore exploit this advantage to extract abnormal returns from outsiders in the stock market. Consequently, it would seem logical that the owners paid less to a management that is allowed to insider trade.

Roulstone (2003, 548–549) studied the role of insider trading in management compensation and found that it has a significant effect. Firstly, firms that restrict insider trading pay higher total compensation for their management. Secondly, firms that restrict insider trading use more incentive-based compensation. The results suggest that insider trading is a way to reduce agency costs of the firm. Although the results are supportive to insider trading, there are also disadvantages.

Padilla (2002, 5) discusses the drawbacks of insider trading from the owners' perspective. Allowing for insiders to trade leads to moral hazard problems, where insiders might have an incentive to manipulate stock price by making bad decisions, spreading false information, and delaying information flow. For example, the management may try to increase the volatility of the stock by increasing the risk level of the firm (Easterbrook 1981, 332). On the other hand, Padilla (2002, 6) argues, that prohibiting insider trading leads to adverse selection problem. Shareholders cannot monitor reliably whether insiders follow the prohibition, which means that untruthful managers are overcompensated for their work. When owners decrease the salaries to resolve the issue, they drive the truthful managers out of the company.

3.4 Signalling theory

Signalling theory focuses on explaining the conduct between two parties who possess varying sets of information. The theory stems from information asymmetry and examines signalling as a way to reduce the issues related to it. (Connelly et al. 2011, 39–40.) Signalling is considered especially useful, if the information asymmetry is linked to the quality or intent of the other party (Stiglitz 2000).

Spence (1973, 356–358) demonstrated the dynamics of signalling in his famous labor market example. He argued, that because employers cannot distinguish productive employees from the lazy ones before hiring, they focus on the signals given by the applicants to maximize the probability of finding a good worker. Applicants can affect some of the signals, such as education, through their own actions and thus increase their probability of being hired. In other words, applicants are signalling their suitability for the job with education. However, not everybody is willing or capable of getting an education, because it usually takes time and money. Therefore, the downside of signalling are the signalling costs involved.

In the insider trading context, insider trades are often viewed as a signal of the future performance of the company. This rationale is based on the earlier finding, that insider trades are associated with abnormal stock returns. When it comes to other performance metrics, Beneish and Vargus (2002, 756) found that insider trading is indicative of the quality of future earnings. John and Lang (1991, 1385) studied insider trading signals around dividend announcements, and found that when announcing for a dividend increase, the price reaction is affected by insider trades. If insiders are net sellers of the stock, price reaction to dividend increase is negative, while in other cases it is positive.

Some studies on signalling have also considered regulatory perspective. Ke et al. (2003, 343) reported increased selling by insiders from nine quarters to three quarters before a break in consecutive earnings increases of the firm. They argued that the absence of increased selling immediately before the earnings break is due to avoiding regulatory risks. This indicates that insiders try to avoid trading restrictions and hide the use of inside information by executing their trades earlier. In contrast, Sivakumar and Waymire (1994, 32) report increased levels of insider trading after earnings announcements. These trades gain abnormal returns for insiders, which indicates that insider trading remains profitable even when trades are restricted to post-announcement periods. In addition, Givoly and Palmon (1985, 85–86) studied underlying reasons behind the price reactions to insider trades and concluded that reactions are due to the information revealed by the trade itself, and not to some piece of news revealed afterwards. This would suggest that illegal insider trading isn’t the primary driver behind the abnormal returns.

In any event, if receivers view signals as credible evidence of quality, it can create an incentive for lower quality signalers to send false signals (Connelly et al. 2011, 46). As insider purchases are usually followed by an increase in stock price, managers might try to manipulate the market and increase the credibility of the company by purchasing stocks even though it would be a bad investment choice. Especially if the investment sums are small, the signalling costs involved might be less than the potential benefits for managers. Therefore, the signal value of a trade should be evaluated carefully.

There are multiple factors that can affect the signal value of an insider trade. Based on market efficiency anomalies, firm size and book-to-market ratios should be considered when reviewing insider trades. Regarding the size of the information asymmetry between insiders and outsiders, position of the insider and ownership structure of the firm might have an impact. When it comes to the trade itself, the volume of the transaction is linked to the information value of trade. Jeng et al. (2003, 468) found that abnormal returns were higher in higher volume purchases. Seyhun (1986, 210) reported similar findings.

Moreover, not all insiders are exploiting their informational advantage in stock market. Cohen et al. (2012) divided insiders into routine traders and opportunistic traders in their study. Routine traders buy and sell stocks usually based on pre-announced plans or as part of their compensation programme, which should make the trades uninformative for outside investors. They found that abnormal returns for routine traders are not different from zero, while opportunistic traders are able to earn abnormal returns and predict future news and events.

To conclude, an example by Miller and Rock (1985, 1032) considering optimal dividend policy under information asymmetry is presented to describe the dynamics of markets with signalling. If investors perceive dividends as signs of unobserved earnings and use that information for valuation purposes, the management has an incentive to increase dividends beyond expectations even at the cost of investments. This leads to short-term price increase, which is reversed when the true state of the firm is revealed. Because of this deception, investors begin to price the risk of false signals to their valuations and new signalling equilibrium is established below the optimal level. Similar adaptation can be expected to happen with insider trading signals.

4 Macroeconomic crises and stock markets

This chapter discusses COVID-19 pandemic and its effects on the stock markets and market uncertainty levels. In addition, previous research on the effects of macroeconomic crises to insider trading is presented.

4.1 COVID-19 pandemic and stock markets

4.1.1 COVID-19 pandemic

On 31 December 2019, the first cluster of pneumonia cases linked to COVID-19 was reported by the Wuhan Municipal Health Commission in China. The first recorded case outside of China was confirmed in Thailand on 13 January, and by the end of the month coronavirus had spread to 18 countries outside China. On 11 March 2020, COVID-19 was characterized as a pandemic by World Health Organization (WHO). (WHO 27.4.2020.)

Countries responded to the spreading coronavirus by introducing restrictions and bans for people and companies. For example, in the United States many of the schools, restaurants and non-essential businesses were required to be closed (Baker et al. 2020). Although strict policies were introduced, the official number of COVID-19 related deaths reported by WHO was around 1.8 million people in the end of 2020. Based on the excess mortality rates, WHO estimated that the real death toll was even higher, at least 3 million people. (WHO 2021.)

In Finland, the first COVID-19 case was identified during the first week of February 2020 (THL 11.12.2023). On March 16, 2020, The Finnish Government, in co-operation with the President of the Republic, declared a state of emergency over COVID-19. Public gatherings were limited to ten persons and many public places such as schools, universities, libraries, and sports facilities were closed. (Valtioneuvosto 16.3.2020.) Less than two weeks after on March 28, the Government introduced restrictions on movement to and from Uusimaa (Valtioneuvoston kanslia 28.3.2020). In addition, on April 3 all restaurants, cafes, and bars were required to be closed (Valtioneuvoston kanslia 3.4.2020).

4.1.2 Stock market crash of 2020

The effects of the pandemic to the global economy and stock markets were unprecedented. Most importantly, COVID-19 caused a global stock market crash in the early spring of 2020. Liu et al. (2020) studied the short-term market responses to COVID-19 in multiple countries and reported steep declines in stock market indices all over the world after the outbreak. Similarly, Erdem (2020) studied responses in 75 countries and reported significant negative reactions with decreasing returns and higher volatilities. For example, in March 2020, the stock prices in the United States collapsed in one of the largest stock market crashes in history (Mazur et al. 2021). The volatility levels in the markets increased to similar levels than in previous stock market crashes of 1987 and 2008 (Baker et al. 2020).

The crash of Finnish stock market is visualized in Figure 1, which presents the performance of the general index (OMX Helsinki) of Nasdaq Helsinki during 2020. The chart is based on values collected from the website of The Bank of Finland. In total OMX Helsinki decreased 36.37 percent during the crash from 11/2/2020 to 18/3/2020 (Suomen Pankki 2023). The worst single day was March 12, when the general index dropped by 10.23 percent (Kauppalehti 12.3.2020). Figure 1 also indicates that the recovery of the market was rapid. OMX Helsinki reached its pre-crash value on 25/11/2020 (Suomen Pankki 2023).

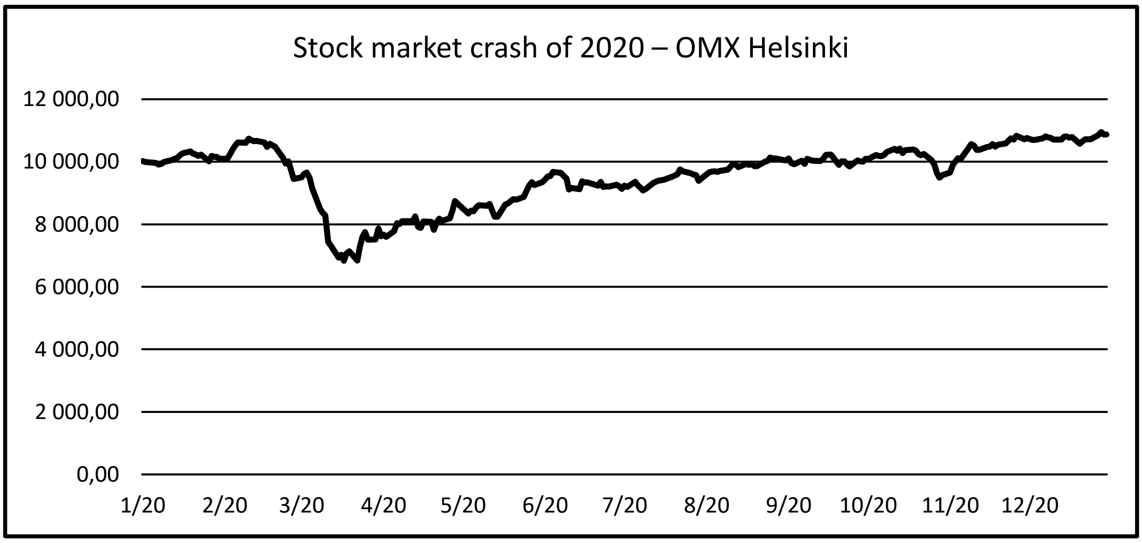

Figure 1. OMX Helsinki 2020 (Suomen Pankki 2023).

Baker et al. (2020) consider the possible reasons for the severe market reactions. They emphasize that previous pandemics, which have had higher mortality rates, have not caused similar reactions. They conclude that health effects, improved information flow in the modern economy, or disruptions to global supply chains are not the primary drivers of the reaction. Instead, the unique political response to the crisis seems to explain the reaction. Baker et al. (2020) argue that the strict restrictions on people's mobility combined with voluntary social distancing had negative effects to service-oriented economy. Mazur et al. (2021) agree by stating that the crash was initiated by the spreading coronavirus and the government's strict response to it, which resulted in reduced consumption and higher unemployment.

However, all the stocks did not experience similar declines during the crash. Mazur et al. (2021) found that stocks in healthcare, food, and software sectors performed rather well while stocks in real estate, entertainment and hospitality sectors performed significantly worse. The response also seemed to be country dependent. Fernandez-Perez et al. (2021) found that countries with low tendency to avoid uncertainty and high individualistic behavior reacted more positively and with lower volatility to the pandemic. Moreover, Erdem (2020) found that the stock market response was more negative in less free countries. A possible explanation for this is that the investors in less free countries are more likely to believe that the published number of COVID-19 cases is understated.

Figure 2 illustrates the stock market reactions of three industry indices to COVID-19 in Nasdaq Helsinki compared to the performance of the general index. All the indices have been adjusted to start from 100 at beginning of 2020. The chart indicates that there are some differences in reactions to the crisis between industries, as suggested by Mazur et al. (2021). Although all the industry indices decreased during the crash, healthcare sector seemed to drop less than finance sector or oil and gas sector. Moreover, finance sector recovered from the crash slower than general index whereas oil and gas sector recovered very strongly.

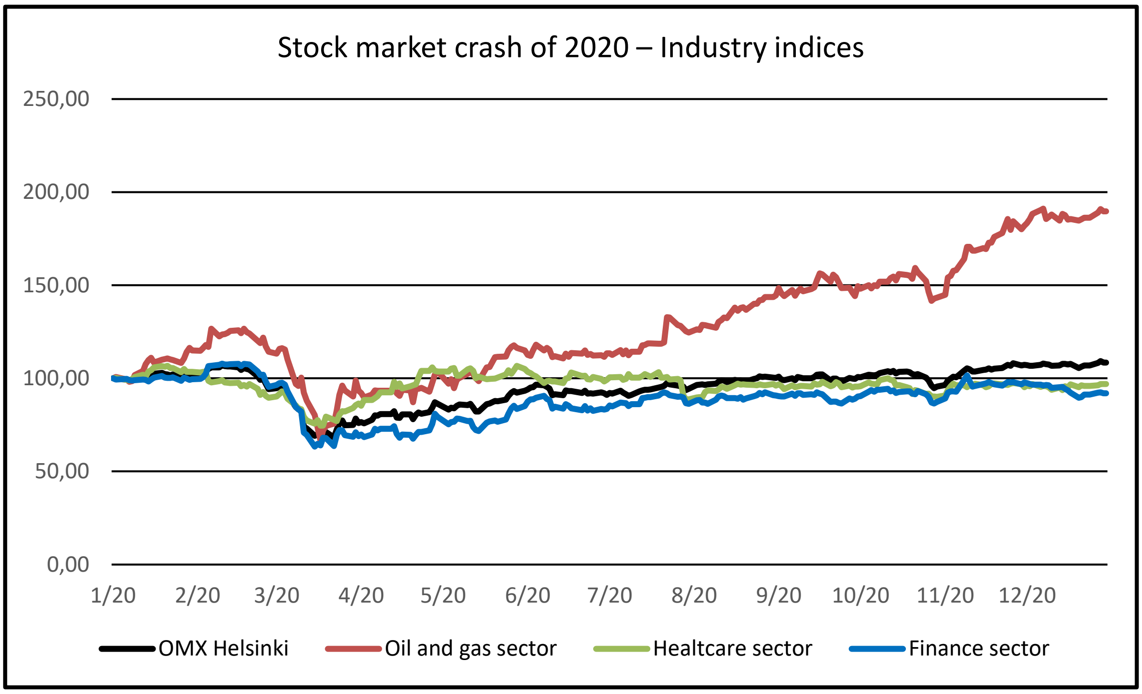

Figure 2. Industry indices 2020 (Suomen Pankki 2023).

An important indicator for the stock markets regarding the pandemic seemed to be the number of confirmed COVID-19 cases. Ashraf (2020) studied stock market responses to COVID-19 in 64 countries and found that stock markets reacted negatively to increases in COVID-19 cases. However, the response to increases in the death toll was weak. Similarly, Erdem (2020) reported that the effect of the number of cases was stronger than the effect of the number of deaths. In addition, there seemed to be a negativity bias in the importance of COVID-19 news. Baek et al. (2020), who reported a significant increase in volatility in the US stock market, found that negative news concerning COVID-19 had a greater impact on the stock markets than positive news.

Regarding the timeline of the pandemic, Phan and Narayan (2020) studied the stock market reactions of 25 countries to different phases of the pandemic. On March 11, when WHO declared COVID-19 a pandemic, the stock market return was negative in 24 of the 25 countries. Announcements of travel bans and stimulus packages in the countries caused more mixed reactions. However, announcements of lockdowns seemed to get primarily a positive response from the markets. Moreover, when it comes to the effects on market efficiency, Wang and Wang (2021) argue that market efficiency decreased in the US stock market during the February and March of 2020. Ozkan (2021) reported similar findings with international data.

4.1.3 Market uncertainty during the pandemic

Although the global stock market crash of 2020 seemed to be over by March, the market uncertainty caused by the pandemic was still present. As reported in section 4.1.1, governments introduced various restrictions and bans for people and companies, which had an impact on the economy. To understand the effects of the pandemic on the uncertainty level of stock markets, two measures, volatility index (VIX) and index of economic policy uncertainty (EPU), are introduced and examined.

Firstly, VIX is a market volatility index, which measures the expected future volatility of US stock markets over the next 30 days. It is calculated by the Chicago Board Options Exchange (CBOE) using current option prices as a signal of market expectations for future volatility. It is commonly known as a "barometer of investor fear" because high expected volatilities indicate that the uncertainty regarding future stock prices is high. Previously VIX has peaked for example during the 1987 and 2008 market crashes. (Whaley 2009.)

Figure 3 shows the performance of VIX from 2019 to 2021. There is a steep increase in the value during the March of 2020 and the peak is achieved on 16 of March. The highest value, 82.69, exceeds the previous record from 2008 (Baek et al. 2020).

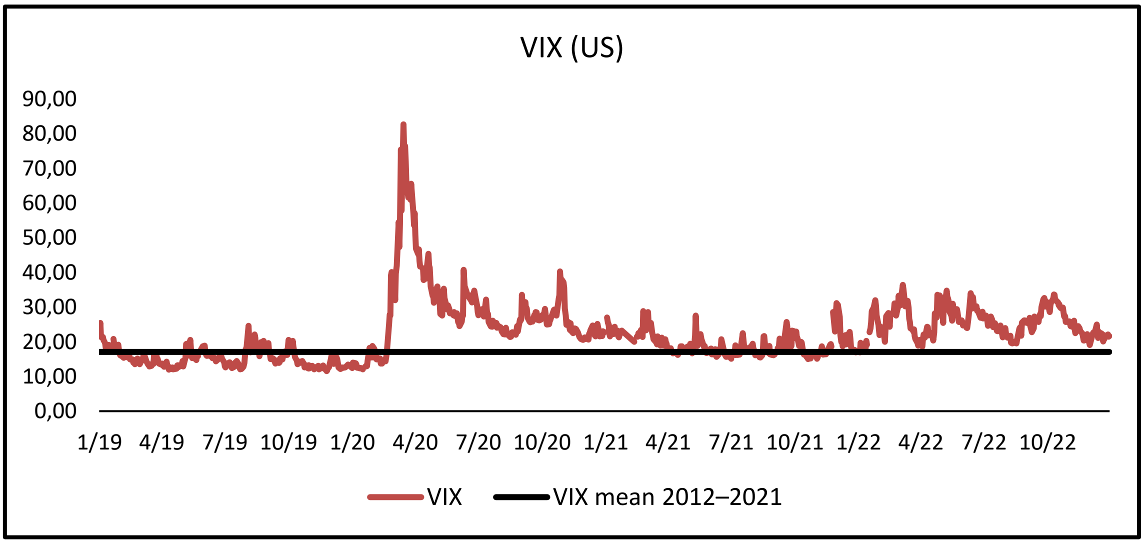

Figure 3. VIX (US) 2019–2021 (Yahoo Finance).

Figure 3 also includes the average VIX value calculated from 2012 to 2021. VIX surpasses this historical mean on February 24, and falls back below it on April 7, 2021 (Yahoo Finance). In contrast to the steep rise of the index, the recovery is slow. This indicates that the uncertainty created by the pandemic is present in the stock market over a year after the crash.

Secondly, EPU is a measure for economic policy uncertainty, which was developed by Baker et al. (2016). It is based on the frequency of certain key words related to economic policy uncertainty found in newspapers. If these themes receive significant coverage, the value of EPU index is high and vice versa. There are several versions of EPU for different countries and policy categories. (Baker et al. 2016.)

Baker et al. (2016, 1613) compared EPU to other measures of uncertainty such as VIX. Although the two measures have a correlation of 0.58, they also have differences. In history, VIX has responded more strongly to events such as Asian financial crisis or downfall of Lehman Brothers, while EPU seems to be more sensitive to political battles over economy, presidential elections, and wars. As political response to COVID-19 had an impact on the stock market reactions, EPU seems to be a suitable proxy for the uncertainty.

Figure 4 presents the performance of daily EPU index in the US between 2019 and 2021. The historical mean of EPU between 2012 and 2021 is also included. The chart shows a steep increase in the index around the market crash of 2020. The historical mean is surpassed on February 28, and the peak is achieved on May 5. Similarly to VIX, EPU index decreased slowly and fell back below the historical mean on January 8, 2021. (Economic Policy Uncertainty.)

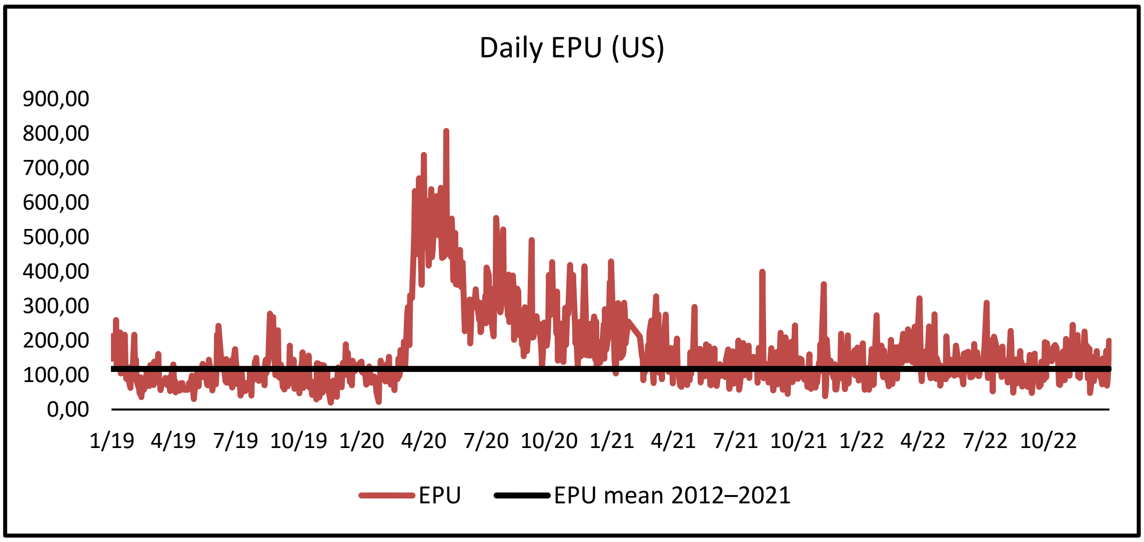

Figure 4. Daily EPU (US) 2019–2021 (Economic Policy Uncertainty).

Although there is a global monthly version of EPU, which considers uncertainty in multiple countries, daily EPU values are only available for the US markets (Economic Policy Uncertainty). As the pandemic rapidly progressed during the first months of 2020, daily values offer a more detailed view of the level of uncertainty. Therefore, daily EPU data from the US is utilized in Figure 4. Moreover, US based EPU is better comparable to VIX, which is also a US based measure.

This thesis focuses on the Finnish stock market, but there are no such uncertainty measures for the Finnish market than VIX or EPU. However, as discussed in section 4.1.2, the global stock market response to the pandemic was very similar worldwide. Moreover, many countries introduced comparable restrictions for individuals and businesses in an attempt to reduce the spread of the virus. Therefore, it's reasonable to assume that US based uncertainty measures are indicative of the uncertainty levels in other developed markets such as Finland.

Performance of VIX and EPU imply that the market uncertainty level rose abruptly in February and March of 2020. The highest value was achieved during the spring of 2020 but the return to normal uncertainty levels happened slowly, and the long-term average level was achieved only during first quarter of 2021. Thus, both VIX and EPU indicate that the uncertainty caused by the pandemic was not limited to the stock market crash of 2020 but was present throughout the year. This conclusion is supported by the results of Bloom (2009, 673–674), who argues that uncertainty increases in the markets after political or economic shocks. He states that shocks have real effects on the companies, as investment and hiring decisions are altered and production levels fluctuate.

4.2 Macroeconomic crises and insider trading

Insider trading approach has been previously used to understand the causes and effects of macroeconomic crises. Firstly, the changes in aggregate insider trading behaviour around crises and market crashes provide insights into insiders' perspectives about real effects of the economic downturns. As insiders are expected to be most knowledgeable of their company, the information value of their trades is high. Secondly, the changes in profitability of insider trades reveal the effects of the crisis to the information asymmetry between insiders and outsiders and market efficiency. Both perspectives have been used in previous research.

Starting with the aggregate insider trading approach, Seyhun (1998, 138–139) studied the reasons behind the stock market crash of October 1987. He suggested that the reactions of insiders to the crash might reveal whether the cause for it was a sudden change in the underlying fundamentals of the market or an overreaction by investors. He presented three scenarios on what happened, which all describe the circumstances in a stock market during the crash.

First scenario was that stocks were valued correctly throughout the crisis. Prices before and after the crash were based on underlying fundamentals and the crash was triggered by an abrupt negative change in those fundamentals. This scenario is also in line with the effective market hypothesis. If the first scenario is true, there should be no strong insider trading before, during or after the crash. However, if insiders are able to get advance information of the negative fundamentals, then an increase in insider selling before the crash would be expected. (Seyhun 1998, 138–139.)

Second scenario was that stock prices increased to unjustified levels prior to the crash and weren't backed by fundamentals anymore. Some event in October 1987 got the market to realize this overvaluation and the prices crashed back to justifiable levels. In this scenario, insiders would have been able to recognize the overvaluation due to their position already before the crash, and therefore increased level of selling is expected before the crash. After the crash, there should be no major changes in the amounts of insider trades, as prices are back to their fundamental levels. (Seyhun 1998, 138–140.)

Lastly, third scenario was that stock prices were correctly valued before the crash, but some event in October 1987 made investors panic and prices crashed under their fundamental values. The expectation in this scenario would be that insider buying would increase after the crash, as prices are lower than the fundamental values of the firms and other investors are selling irrationally. (Seyhun 1998, 138–140.)

The insider trading evidence suggest that in the case of 1987 stock market crash, the third scenario was the most likely. Insiders bought stocks in record numbers after the crash but didn't foresee the crash and sell stocks before the decline. (Seyhun 1998, 143–145.) The scenarios presented are also applicable for stock market crash of 2020. While the trigger for this crash can be identified as the COVID-19 pandemic, only the reactions of insiders, as considered in the first research question, will indicate whether the decline was justified by fundamentals in their view.

Regarding 1987 crash, Seyhun (1990, 1386–1387) also found that stocks that were bought the most by insiders during the crash showed better returns in 1988 compared to other stocks. Moreover, the more the stock price had declined during the crash the more insiders bought it. Consequently, insiders seemed to be able to identify the stocks that deviated the most from their fundamental value during the crash. However, some of the post-crash returns of the insiders are explained by contrarian investment strategy.

There are also contrasting results regarding insiders' ability to identify crashes in advance. Marin and Olivier (2008) studied insider trading activity before large price jumps in the stock market. They found that insider sales peak many months before a crash, while insider purchases peak right before an increase. Thus, insider purchases signal price increases in the near future, whereas high number of insider sales is followed by a period of lower intensity of sales before the crash. Marin and Olivier (2008, 2433) argue that the absence of insider sales might therefore be even worse signal to outside investors than moderate selling activity.

When it comes to the profitability of insider trading during macroeconomic crises, the research is scarce. Van Geyt et al. (2013, 380) focused on the impact of financial crisis on insider trading profitability in the Belgian stock market. According to their results, insiders in Belgium gain abnormal returns in general but the trading was significantly more profitable during financial crisis. This indicates that the information asymmetry between insiders and outsiders might increase in volatile markets and the efficiency of the markets might decrease.

Gangopadhyay et al. (2009, 60) studied the profitability of insider trading during the stock market crash of the early 2000s. They concluded that insider trading is profitable in volatile markets due to superior information of insiders. Also, Lim et al (2008, 588) found that the financial crisis of 1997 had a negative impact on the efficiency of eight stock markets in Asia. They argue that the higher inefficiency might have been due to investors overreacting to news and rumours.

Regarding COVID-19, Henry et al. (2022) studied the trades of insiders who had connections to China at the time of the pandemic. They found that stock sales of such insiders were more profitable during the pandemic than those with no China connections. China connected insiders seemed to execute bigger sales earlier in the pandemic than others. Henry et al. (2022) argue that insiders with connections to China were able to predict the stock market effects of the virus due to their connections, and emphasize the importance of geographic component in insiders' information advantage.

5 Data and methodology

This chapter presents the data and the methodologies used in the empirical part of the thesis. Moreover, methods for evaluating the robustness of the results are presented.

5.1 Data

5.1.1 Insider trading data

Insider trading data for the empirical part of the thesis has been acquired from the Finnish competent authority Finanssivalvonta, which holds an electronic database of the trades. Initially, there are 51,987 rows, further referred to as data points, in the insider transaction data covering the period from January 1, 2019, to December 31, 2021. Before manually verifying data points, the following filters are applied to the data.

- Market: Only transactions from the main list of Nasdaq Helsinki are included. While most data points come from this source, notable data also originates from other markets such as Nasdaq First North Growth Market for smaller companies and CBOE Europe, which focuses on options trading. In addition, off-exchange transactions are excluded.

- Transaction type: Only transactions labelled as "acquisition" or "disposal" are included. They form over 90% of the data. Other transaction types include for instance share-based incentives and subscriptions of stock offerings.

- Companies and ISIN codes: Only companies that have been listed in the main list from 1/1/2019 to 31/12/2021 are included. Companies that have changed their name or participated in a merger are included if their ISIN code has remained the same. An ISIN code is a unique and international identifier for securities and financial instruments (Euroclear Finland). Data points that have no ISIN code are excluded from the data.

- Other details: Some data points include additional information suggesting that the transaction is executed under asset management, life insurance, or linked to an option program. These data points are excluded from the data.

After filtering the data, 24,510 data points remain. Although each data point represents a separate transaction, many of them can be linked together. For instance, an insider might make multiple purchases (disposals) of his firm's stock on the same day through separate transactions. As the timing of intra-day purchases is irrelevant for the purposes of this thesis, such data points can be aggregated on a daily basis. Consequently, aggregated transaction price is the weighted average of individual transaction prices. However, intra-day acquisitions and disposals are not offset against each other. After aggregation, there are 1,689 aggregated transactions in the data.

All transactions are individually verified by comparing them to the press releases concerning managers' transactions. These press releases are viewed from the Central Storage Facility of Nasdaq (Nasdaq Central Storage Facility). In rare cases, also the webpages of the companies are used to gather additional information. The transactions that cannot be verified are excluded from the data. Moreover, transactions found in the press release storage but not present in the original data are added to the dataset. The original data does not include notification dates and thus those are added manually during the verification process.

After verification, the data consists of 1,256 transactions. During verification process, some additional filters are used to ensure the signal value of the transactions. Firstly, insider transactions executed by listed companies, state owned investment companies, pension insurance companies, co-operatives, foundations, and registered associations are excluded from the data. However, transactions executed by the insiders through their personal investment companies are included.

Secondly, multiple firms, such as Fortum Oyj, Konecranes Oyj and Nokia Oyj, have an employee share savings plan, where top officials have a possibility to use a part of their salary to purchase stocks on a quarterly basis and are then rewarded with additional shares by the company. Similarly, some transactions are executed according to a predetermined purchase program. Both transaction types are expected to be uninformative for the purposes of this thesis and are therefore excluded from the data.

The rationale for applying the presented filters to the data during verification is that this thesis focuses on transactions executed by insiders using their own money and on their own schedule, which are perceived to be the most informative. However, this does not imply that the filtered events would be completely uninformative. Omitting these observations constitutes a limitation of the study, which affects the results.

Descriptive statistics of the verified insider trading data are presented in Table 2.

Table 2. Descriptive statistics of insider trading data 2019–2021.

Descriptive statistics	**All**	**Acquisitions**	**Disposals**
Number of transactions	1,256	812	444
Number of stocks	100	92	66
Number of companies	95	88	66

Table 2 indicates that most transactions in the data are acquisitions and many companies and stocks have only been purchased during the sample period. The number of stocks is higher than the number of companies as some companies have multiple stock classes, which insiders have traded.

For each transaction, the final data includes, the name of the company, the name of the stock, the transaction date, the notification date, the position of the insider, the type of the transaction, the transaction price, and the transaction volume. Insiders are classified to five groups based on their position, and these groups are CEOs, CFOs, Board members, other senior managers, and closely associated persons. The type of the transaction is either acquisition or disposal. By multiplying the transaction price with the transaction volume, a monetary size variable for each transaction is created.

5.1.2 Other data

Other data needed in the empirical part of the thesis includes historical stock price and stock market index data, market capitalization data, and price-to-book ratio data from Nasdaq Helsinki. This information is collected using LSEG database, formerly known as Refinitiv Eikon. Instead of simple historical prices, total return series, which account for stock splits and dividends, are used when calculating the historical returns for stocks and indices. The primary index used in beta estimations of the thesis is the value weighted general index (OMXHPI), however also the data for the index consisting of the 25 most traded stocks (OMXH25) is downloaded for robustness checks.

Both simple net returns and logarithmic returns are calculated for the stocks and indices following formulas from Vaihekoski (2016). Net returns are calculated using the equation

$$R_t = \frac{P_t}{P_{t-1}} - 1, \tag{1}$$

where R_t is the net return for the day t, and P_t is the value of the total return index on the day t. Similarly, logarithmic returns are formed using the equation

$$r_t = \ln \frac{P_t}{P_{t-1}}, \tag{2}$$

where r_t is the logarithmic return for the day t, and P_t is the value of the total return index on the day t. Further in this thesis, simple net returns are referred to with R and logarithmic returns with r. The benefits of logarithmic returns, which are also called continuously compounded returns, are that they tend to follow a more normal distribution than simple net returns, which is beneficial in statistical analysis. Moreover, they can simply be added together to form the cumulative return for a longer time period. (Vaihekoski, 2016.)

For market capitalizations and price-to-book ratios of the companies, year-end values from 2018, 2019 and 2020 are used. The data is verified by comparing it to the information in Kauppalehti webpage (Kauppalehti Pörssi). When needed, the annual reports of companies are used for additional verification.

5.2 Methodology

5.2.1 Insider trading ratio approach

The first and the second research question of the thesis focus on the overall behaviour of insiders around the stock market crash of 2020. The answers to the questions are derived from the changes in aggregate insider trading data and do not include firm-level analysis. The methodology used in both questions follows Seyhun (1990).

Seyhun (1990, 1366) applies a ratio-based approach to analyse the changes in aggregate insider trading. The idea of the approach is to proportion the level of purchasing activity relative to the total insider trading activity during a specific time period. According to Seyhun (1990, 1366) the advantages of the approach are that “ratio is not sensitive to changes in the number of firms or trading activity over time” and that it “does not display heteroscedasticity or extreme outliers”. He uses two ratios in his study. The first insider trading ratio is frequency based and defined as

$$PRAT = \frac{NP}{(NP+NS)}, \tag{3}$$

where *NP* refers to number of purchases, and *NS* is number of sales. The second ratio is volume-based, and it is calculated by dividing the number of shares purchased with the number of shares purchased and sold by insiders. The equation is

$$SPRAT = \frac{SP}{(SP+SS)}, \tag{4}$$

where *SP* refers to shares purchased, and *SS* is shares sold.

To get a comprehensive understanding of the aggregate insider trading behaviour around the crash, also a third purchase ratio is created for the purposes of this thesis. It focuses on the aggregate monetary value of the transactions. The ratio is defined as

$$EPRAT = \frac{EP}{(EP+ES)}, \tag{5}$$

where *EP* refers to euros purchased, and *ES* is euros sold. A monetary size variable is created for each transaction as described in section 5.1.1.

5.2.2 Time series regression models

The first research question of the thesis is: How did corporate insiders respond to the stock market crash of 2020? To analyse the significance of the changes in the insider trading ratios and insider trading variables before, during and after the crash, Seyhun (1990) estimates time series regression models. Insider trading measures are the dependent variables in the models and the independent variables are dummy variables for the time periods around the crash. The changes in the ratios are examined on a monthly level. Moreover, autocorrelation of the models' residuals is tested to satisfy the Gauss-Markov assumptions.

In this thesis, the ratios *PRAT*, *SPRAT* and *EPRAT* for the purposes of the first research question are calculated after aggregating the insider trades on a biweekly basis (10 trading days) using the original data. This leads to a sample size of 79 observations. Analysing the changes on a two-week periods is expected to illustrate insiders' response to the crash sufficiently. Using daily or weekly trading data would cause problems because there are days and weeks with no insider trades in the Finnish stock market. The time series regression equation used in estimation is

$$Insider\ trading\ ratio\ or\ variable = \alpha_0 + \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \varepsilon, \tag{6}$$

where α_0 is the constant, α_1, α_2 and α_3 are the regression coefficients, ε is the error term, D_1 is the dummy variable for pre-crash period, D_2 is the dummy variable for crash period, and D_3 is the dummy variable for post-crash period. The time periods are defined as follows:

- Pre-crash period: 30/12/2019–9/2/2020 (6 weeks, 26 trading days)
- Crash period: 10/2/2020–22/3/2020 (6 weeks, 30 trading days)
- Post-crash period: 23/3/2020–3/5/2020 (6 weeks, 29 trading days)

The crash period is defined based on the performance of Finnish stock market. The general index of Nasdaq Helsinki recorded its highest value during the spring of 2020 on Tuesday February 11 and lowest on Wednesday March 18 (Suomen Pankki 2023). Since trading ratios are calculated on a biweekly basis, the crash period includes also one trading day before the crash and two trading days after the crash. The total length of the crash period is 6 weeks and 30 trading days. Pre-crash and post-crash periods match the length of the crash period. They are determined to identify changes in the insider trading behavior before and after the crash.

5.2.3 Weighted least squares regression models

The second research question of the thesis is: What was the post-crash performance of the stocks that insiders traded during the market crash? The methodology used to answer this question follows Seyhun (1990). He estimates a weighted least squares regression model (WLS), where the post-crash returns of a group of stocks are explained by the changes in insider trading ratios during the crash. In addition, the return from the crash period, the pre-crash estimation of firms' beta, and the logarithm of the market capitalization of the firms are included as independent variables in the equation. The grouping is based on the values of the independent variables, and the weights for the estimation are the number of observations in each group. The reason for the grouping is that insiders do not trade individual companies monthly, and therefore insider trading variables cannot be identified.

In this thesis, a similar approach is used but some adjustments are made. Seyhun (1990) controls for size anomaly and contrarian anomaly of the returns by using market capitalizations and crash returns as independent variables. However, value effect is not considered and therefore a new variable, price-to-book ratio, is added to the regression equation of this thesis. Also, instead of monthly aggregation of variables similarly to Seyhun (1990), the daily insider trading variables are summed for each company in six-week periods. The cycle of these periods is chosen in a way that that all the trades during the crash period of 2020 are combined. The crash period was defined in section 5.2.1. The reason for the longer aggregation period is the smaller sample size of this thesis compared to Seyhun (1990). Due to the six-week aggregation interval, the trades from the first four weeks of 2019 and the last two weeks of 2021 are excluded from the sample.

The equation for weighted least squares regression used in this thesis is

$$R_{pc} = \alpha_0 + \alpha_1 \Delta\, Insider\ trading\ ratio + \alpha_2 R_c + \alpha_3 \beta + \alpha_4 MC + \alpha_5 PB + \varepsilon, \tag{7}$$

where R_{pc} refers to the simple average post-crash net return of the group, Δ *Insider trading* is the change in insider trading ratio during the crash period, R_c refers to the simple average crash net return of the group, β is the average beta of the group, *MC* is the natural logarithm of average market capitalization of the group, *PB* refers to the average price-to-book ratio of the group, α_0 is the constant, α_1, α_2, α_3, α_4, α_5 are the regression coefficients, and ε is the error term. The number of companies in each group is used as the weights in the regression model.

The data for the regression variables is collected and created as follows. Market capitalizations and price-to-book ratios are collected for each stock from the end of 2019. Beta estimates for each stock are calculated using the data from all trading days (250 days) of 2019 and following the formula presented by Vaihekoski (2016)

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}, \tag{8}$$

where β_i is the beta for stock i, r_i is the logarithmic return for stock i, and r_m is the logarithmic return for the market portfolio. Market portfolio used in the estimation is OMXHPI. Crash returns are defined as the simple net returns from 10/2/2020 to 22/3/2020 and calculated for each stock. Similarly, post-crash returns are calculated for three intervals, 6 months (22/3/2020–22/9/2020), 12 months (22/3/2020–22/3/2021), and 18 months (22/3/2020–22/9/2021).

Before calculating the changes in insider trading ratios, the firms are grouped into nine portfolios based on their market capitalization and price-to-book ratios. In the Finnish stock market, a large-cap company is defined as having a market capitalization of over one billion euros. Mid-cap companies have a market capitalization of over 150 million euros, while small-cap companies are valued below that threshold. (Nasdaq Market Cap 20.12.2017.) These classes are used for size grouping. Regarding price-to-book ratio grouping, the stocks are organized into descending order by the ratio and equally split to three groups labelled high PB, mid PB and low PB. However, Nurminen Logistics Oyj and SSH Communications Security Oyj had a negative price-to-book ratios in the end of 2019 due to negative book values. As negative ratios would be clear outliers in the low PB group, both companies are excluded from the data.

Returns, betas, market capitalizations and price-to-book ratios of the groups are calculated as simple averages of the stocks in the groups. Due to a smaller sample size than Seyhun (1990), not all independent variables can be used when forming the groups. Therefore, high and low crash returns and betas might cancel each other out within the groups, which affects the reliability of the coefficients regarding these measures.

After grouping, the changes in the insider trading ratios for each group can be calculated with the equation

$$\Delta\text{Insider trading ratio} = \frac{Insider\ trading\ ratio_c - Insider\ trading\ ratio_{avg}}{Standard\ deviation\ of\ insider\ trading\ ratio}, \tag{9}$$

where *ΔInsider trading ratio* is the change in ratios *PRAT*, *SPRAT*, or *EPRAT* of the group, $Insider\ trading\ ratio_c$ is the ratio of the group during the crash period, and $Insider\ trading\ ratio_{avg}$ is the average ratio of the group during the six-week periods from 2019 to 2021.

5.2.4 Event study methodology

The third research question of the thesis is: How did the COVID-19 pandemic affect the profitability of insider trading? To answer the question, event study methodology is used to determine the profitability of insider trades, before analysing the changes using statistical methods. The event study approach has also been used in majority of the insider trading studies presented in Table 1 in section 2.3.1.

The basic structure of an event study is as follows. Firstly, an interesting event, which is expected to influence the stock price of a company, is identified. In this thesis, these events are insiders' trades and event dates are the transaction dates. Secondly, the effect of the event to the stock price of the firm is examined by analysing the stock returns on the days around the event day. To isolate the effect the event from the actual returns, abnormal returns are calculated by deducting normal returns from the actual returns. In other words, the normal returns are estimated to be the returns observed if the event had not occurred. (MacKinlay 1997, 14–15.)

Although the basic structure is simple, there are multiple choices to be made when conducting an event study. Most importantly, the model for predicting the normal returns has to be chosen. Event studies suffer from the joint-hypothesis problem, which was introduced in section 3.1.2, and thus the performance of the model is important for the results. MacKinlay (1997, 17–19) presents multiple models for predicting normal returns including constant mean return model, market model, and CAPM. In addition to choosing the model, the length of the estimation and measurement periods need to be defined. The period for estimating the parameters of the chosen normal return model is called estimation window, while the period for calculating the abnormal returns is called the event window (MacKinlay 1997, 20).

Following Van Geyt et al. (2013, 372) standard market model and Dimson-adjusted market model are used to estimate the normal returns for the stocks in this thesis. Already in 1960s, Fama et al. (1969, 4) introduced the standard market model, which assumes that there is a linear relationship between the stock return and the market return. Since then, market model has been widely used in research, which can also be seen in Table 1 in section 2.3.1.

The parameters for the market model are estimated similarly to Van Geyt et al. (2013, 372). Since there are multiple events for the same companies in the data, some of which overlap, the parameters are estimated for each event individually instead of at the firm-level. A unique identifier e is used for each event in the following equations, referring to a certain event for a specific company in the dataset. The equation used in the estimation is

$$r_{e,t} = \alpha_e + \beta_e r_{m,t} + \varepsilon_{e,t}, \tag{10}$$

where $r_{e,t}$ is the daily logarithmic return for the firm of the event e on the day t, $r_{m,t}$ is the daily total return for the market index on the day t, α_e and β_e are the estimated coefficients that are used in forecasting the normal returns and $\varepsilon_{e,t}$ is the error term for the event e on the day t.

However, Dimson (1979, 197) argued that the beta estimates of the market model are often biased for stocks that are traded infrequently. He suggested that this bias can be alleviated by adding lagged and leading market returns to the market model. Following Van Geyt et al. (2013, 372) three lagged and one leading coefficient are added to the market model, which is used for thinly traded stocks. The Dimson adjusted market model parameters are estimated as

$$r_{e,t} = \alpha_e + \sum_{k=-3}^{1} \beta_{e,k} r_{m,t+k} + \varepsilon_{e,t}, \tag{11}$$

where $r_{e,t}$ is the daily logarithmic return for the firm of the event e on the day t, $r_{m,t+k}$ is the daily total return for the market index on the day t and days $t+k$, α_e and $\beta_{e,k}$ are the estimated coefficients that are used in forecasting the normal returns and $\varepsilon_{e,t}$ is the error term for the event e on the day t.

The length of the estimation window used for both models in this thesis is 160 trading days similarly to Van Geyt et al. (2013). However, the estimation window ends 10 trading days before the event date similarly to MacKinlay (1997, 20), who argues that this ensures that the returns around the event do not affect the parameters of the normal return model. Thus, the estimation window spans from trading day 170 to day 11 before the event.

The thinly traded stocks are identified similarly to Friederich et al. (2002) and Van Geyt et al. (2013). The stocks in the sample are organized in descending order based on the average number of zero return days during the estimation periods of their events. For the events of the stocks in the highest quarter, the Dimson adjusted market model is used, while for other stocks, the standard market model is employed.

Similarly to Van Geyt et al. (2013, 372) the estimated parameters are used to calculate the abnormal returns for each event. The equation used for stocks accompanied with the standard market model is

$$AR_{e,t} = r_{e,t} - \hat{\alpha}_e - \hat{\beta}_e r_{m,t}, \tag{12}$$

where $AR_{e,t}$ refers to the abnormal return for the event *e* on the day *t*, $r_{e,t}$ refers to the actual return for the firm of the event *e* on the day *t*, $r_{m,t}$ refers to the return for the market index on the day *t*, and $\hat{\alpha}_e$ and $\hat{\beta}_e$ are the estimated parameters for the event *e*. For thinly traded stocks, the equation is

$$AR_{e,t} = r_{e,t} - \hat{\alpha}_e - \sum_{k=-3}^{1} \hat{\beta}_{e,k} r_{m,t+k}, \tag{13}$$

where $AR_{e,t}$ refers to the abnormal return for the event *e* on the day *t*, $r_{e,t}$ refers to the actual return for the firm of the event *e* on the day *t*, $r_{m,t+k}$ refers to the return for the market index on the day *t* and days *t+k*, and $\hat{\alpha}_e$ and $\hat{\beta}_{e,k}$ are the estimated parameters for the event *e*.

The length of the event window follows Van Geyt et al. (2013, 372) and is 21 trading days (day 0 to day 20). The cumulative abnormal return (CAR) and cumulative average abnormal return (CAAR) are calculated similarly to Van Geyt et al. (2013, 373). The equation for CAR is

$$CAR_{\{e,(0,20)\}} = \sum_{t=0}^{20} AR_{e,t}, \tag{14}$$

where $CAR_{\{e,(0,20)\}}$ refers to the cumulative abnormal return for the event *e*, and $AR_{e,t}$ refers to the abnormal return of the event *e* on the day *t*. Lastly, the equation for CAAR is

$$CAAR_{(0,20)} = \frac{1}{N} \sum_{e=1}^{N} CAR_{\{e,(0,20)\}}, \tag{15}$$

where $CAAR_{(0,20)}$ refers to the cumulative average abnormal return, $CAR_{\{e,(0,20)\}}$ refers to the cumulative abnormal return for the event *e*, and *N* is equal to the number of events.

5.2.5 Ordinary least squares regression model and t-tests

The changes in profitability of insider trading during the COVID-19 crisis are analysed following Van Geyt et. (2013). Firstly, the crisis period is defined. Based on the uncertainty measures VIX and EPU presented in section 4.1.3, the uncertainty levels rose above the long-term average levels during the first quarter of 2020 and fell back below them during the first quarter of 2021. Also, COVID-19 started to spread at the beginning of 2020. Therefore, the crisis period is defined from 1/1/2020 to 31/3/2021 including 5 quarters. The non-crisis period spans from 1/1/2019 to 31/12/2019, and from 1/4/2021 to 31/12/2021.

Secondly, the variables used in the tests are presented as a list below.

- $CAR_{(0,20)}$: Cumulative abnormal return from the event day and following 20 trading days, which is calculated for each event using the event study methodology. The variable is tested both separately for purchases and sales and jointly. $CAR_{(0,20)P}$ refers to CARs of purchases only and $CAR_{(0,20)S}$ to sales only. When testing the variable jointly, CARs for disposals are multiplied by –1 as they model the avoided losses of the insiders.

- Control variables: Control variables include trade size, which is referred to as *TS*, market capitalization denoted as *MC*, and price-to-book ratio referred to as *PB*. For *MC*, which is reported in billions of euros, and *PB,* the closest year-end values preceding the event are used. *TS* is calculated by dividing the monetary value of the trade with market capitalization. In addition, total number of trades on the event day and the lag between the event day and the notification day are calculated for controlling purposes. These are referred to as *NoT* and *Lag* respectively.

- Crisis dummy variables: *Crisis* is a dummy variable, which indicates crisis period with value one and zero otherwise. For more detailed analysis individual dummy variables for all 5 quarters of the crisis period are created. These are *Crisis_Q1_20*, *Crisis_Q2_20*, *Crisis_Q3_20*, *Crisis_Q4_20*, *Crisis_Q1_21.*

- Position of the insider: Dummy variables for CEOs, CFOs, Board members, other senior managers, and closely associated persons are created to indicate the type of insider involved in the event. Variables are named *CEO*, *CFO*, *MoB*, *OSM*, and *CAP*. Fifth group of insiders, closely associated persons, is used as the reference group in the regressions. For more detailed analysis, interaction variables between insider types and crisis period are created by multiplying the dummy variables with each other. Interaction variables are *CEO_Crisis*, *CFO_Crisis*, *MoB_Crisis*, *OSM_Crisis*, and *CAP_Crisis.*

- Sales dummy variable: Dummy variable *Sales* is created to identify disposals from all the events. Variable is not used in regressions but in forming the samples of CARs for purchases and sales only.

While preparing the data for analysis, negative *PB* values are associated with few events due to negative book values of the companies in the end of the preceding year. As these values would be clear outliers in the data, all 27 events with negative ratios are excluded from the data. Thus, the final sample consists of 1229 events.

Thirdly, following Van Geyt et al. (2013) univariate t-tests are used to test whether the mean values of the chosen variables calculated from the crisis period and non-crisis period are significantly different from each other. The null hypothesis of the t-test is that the means of the two populations are equal (Wilcox 2016, 265). As mean values might be driven by single outliers, test for medians is also conducted. Van Geyt et al. (2013) use Mann-Whitney U test to test the difference between median values of the two groups. However, Wilcox (2016, 289) argues that rank-based Mann-Whitney U test does not actually compare medians but could be better described as a test for whether the distributions of the populations are identical. This notion is considered when interpretating the results. The null hypothesis for the Mann-Whitney U test is that the distributions are equal.

Fourthly, multiple ordinary least squares regressions (OLS) are estimated to analyse the profitability of insider trading similarly to Van Geyt et al. (2013). In contrast to their study, all regression models are estimated separately for the samples including all transactions, only purchases, and only sales, as this provides more detailed outlook on the profitability than including only dummy variable for sales in the equations. The first OLS regression is estimated to test whether insiders get significant abnormal returns during the total sample period. The equation is

$$CAR_{(0,20)} = \alpha_0 + \varepsilon, \tag{16}$$

where $CAR_{(0,20)}$ is explained by a single constant α_0, and ε is the error term. Similar regressions are estimated for the series of CARs consisting of purchases and sales only. To test for the effect of the control variables on the insider trading profitability, the second OLS regression including control variables is estimated. The equation is

$$CAR_{(0,20)} = \alpha_0 + \sum_{i=1}^{5} \beta_i Controls + \varepsilon, \tag{17}$$

where α_0 is constant, β_1 to β_5 are the coefficients, ε is the error term, and *Controls* is a vector consisting of control variables *TS*, *MC*, *PB*, *NoT*, and *Lag*. Similar regressions are estimated for the series of CARs consisting of purchases and sales only. The third OLS regression tests whether the COVID-19 crisis affected the profitability. The equation is

$$CAR_{(0,20)} = \alpha_0 + \beta_1 Crisis + \sum_{i=2}^{6} \beta_i Controls + \varepsilon, \quad (18)$$

where α_0 is constant, β_1 to β_6 are the coefficients, ε is the error term, *Crisis* is the dummy variable for the crisis period, and *Controls* is a vector consisting of control variables *TS*, *MC*, *PB*, *NoT*, and *Lag*. Similar regressions are estimated for $CAR_{(0,20)P}$ and $CAR_{(0,20)S}$. As the market conditions changed during the crisis period from stock market crash of March 2020 to a rapid recovery period, a regression model with more detailed view on the quarterly changes during the crisis period is estimated. The equation is

$$CAR_{(0,20)} = \alpha_0 + \sum_{i=1}^{5} \beta_i CrisisQuarters + \sum_{i=6}^{10} \beta_i Controls + \varepsilon, \quad (19)$$

where α_0 is constant, β_1 to β_{10} are the coefficients, ε is the error term, *CrisisQuarters* is a vector consisting of dummy variables *Crisis_Q1_20*, *Crisis_Q2_20*, *Crisis_Q3_20*, *Crisis_Q4_20*, *Crisis_Q1_21*, and *Controls* is a vector consisting of control variables *TS*, *MC*, *PB*, *NoT*, and *Lag*. Similar regressions are estimated for $CAR_{(0,20)P}$ and $CAR_{(0,20)S}$.

Lastly, the effect of the of the position of the insider to the profitability of the trades is examined with two OLS regression models. The first one includes dummy variables for four of the five insider types. The equation is

$$CAR_{(0,20)} = \alpha_0 + \beta_1 Crisis + \sum_{i=2}^{5} \beta_i Pos + \sum_{i=6}^{10} \beta_i Controls + \varepsilon, \quad (20)$$

where α_0 is constant, β_1 to β_{10} are the coefficients, ε is the error term, *Crisis* is the dummy variable for the crisis period, *Pos* is a vector consisting of dummy variables *CEO*, *CFO*, *MoB*, *OSM*, while the trades of the closely associated persons are used as the reference group. Moreover, *Controls* is a vector consisting of control variables *TS*, *MC*, *PB*, *NoT*, and *Lag*. Similar regressions are estimated for $CAR_{(0,20)P}$ and $CAR_{(0,20)S}$.

However, this equation assumes that the difference in profitability of the trades of a specific insider group and closely associated persons is the same during crisis and non-crisis period. To account for the variability in profitability differences between the periods, interaction variables between crisis dummy variable and insider position dummy variables are added to the formula. The equation is

$$CAR_{(0,20)} = \alpha_0 + \beta_1 Crisis + \sum_{i=2}^{5} \beta_i Pos + \sum_{i=6}^{9} \beta_i PosC + \sum_{i=10}^{14} \beta_i Controls + \varepsilon, \quad (21)$$

where α_0 is constant, β_1 to β_{14} are the coefficients, ε is the error term, *Crisis* is the dummy variable for the crisis period, *Pos* is a vector consisting of dummy variables *CEO*, *CFO*, *MoB*, *OSM*, while the trades of the closely associated persons are used as the reference group. *PosC* is a vector consisting of the interaction dummy variables *CEO_Crisis*, *CFO_Crisis*, *MoB_Crisis*, and *OSM_Crisis*. Moreover, *Controls* is a vector consisting of control variables *TS*, *MC*, *PB*, *NoT*, and *Lag*. Similar regressions are estimated for $CAR_{(0,20)P}$ and $CAR_{(0,20)S}$.

5.2.6 Methods to determine statistical significance

Multiple regression models are estimated in the thesis and thus the statistical significance of the results needs to be determined. The significance of individual regression coefficients of the estimated models is tested with a two-tailed t-test. T-statistic for the coefficient is formed by dividing the estimated coefficient value with the standard error of the coefficient. T-statistic is then paired with a corresponding p-value using t-distribution and degrees of freedom. (Wooldridge 2020, 120–130.)

Null hypothesis of the t-test is that the coefficient is zero and the independent variable does not have a statistically significant relationship with the dependent variable. If the p-value is low enough, the null hypothesis can be rejected, and the coefficient is statistically significantly different from zero. Whether p-value is low enough depends on the chosen significance level. If the significance level is 5%, it means that the risk of rejecting the null hypothesis even if it was true is 5%. There is no universal rule for the desired significance level, but 5% is a commonly used level. (Wooldridge 2020, 120–130.) In this thesis, p-values below 5% are considered significant, and all p-values under 10% are reviewed with special attention.

In addition to testing the significance of the individual coefficients, F-test can be used to test all the coefficients in the model jointly. The null hypothesis of the test is that all the model coefficients are equal to zero. Error terms of the model, also known as residuals, are used for calculating the F-statistic. (Wooldridge 2020,139.) Another way to evaluate the goodness of fit of models is to inspect the R-squared value, which indicates in percentage how much of the variation in the dependent variable the model explains (Wooldridge 2020, 35). The adjusted R-squared value is a similar measure, but it also considers the number of independent variables in the model and penalizes for adding new variables, if they are not informative (Wooldridge 2020, 196–197). R-squared values and F-test results are reported for selected regression models.

Alongside statistical significance, the economic significance of the regression results is also considered. A regression coefficient might be statistically significant but is still so close to zero that the effect of the independent variable to the dependent variable is marginal. This means that the economic significance of the result is low. Wooldridge (2020, 132) states that the economic significance of the result can be assessed by reviewing the size and sign of the coefficient estimate. Considering economic significance in addition to statistical significance ensures that the results also have practical importance.

Moreover, Wooldridge (2020, 133) presents an issue of significance testing related to small samples. As described earlier, t-test results are based on the t-statistic, which is calculated using the coefficient estimate and the standard error of the estimate. Thus, a statistically significant finding can be due to a large coefficient value or a low standard error. By addressing the economic significance of the results, a distinction between these scenarios can be made. However, when the sample size is small, the standard errors are usually relatively large compared to the coefficients, which can lead to insignificant p-values even when the coefficients are large. Consequently, some researchers use higher significance levels with small samples to correct for this effect. (Wooldridge 2020, 133.) The issue of small samples is considered in the thesis when interpreting the results of the WLS regressions, where the sample size is very small.

5.3 Robustness of the results

5.3.1 Regression model robustness

Linear regression models are the primary analysis method of the thesis, and therefore robustness of the models needs to be addressed. Time series regression models and OLS regression models of the thesis are estimated using the ordinary least squares technique. Moreover, WLS regression is an extension of the original OLS regression. The Gauss-Markov theorem proves that OLS technique produces the best estimates for the model coefficients. However, the theorem has several underlying assumptions. (Nirmal Ravi Kumar 2020, 199).

Robustness tests of this thesis focus on the selected Gauss-Markov assumptions related the residuals of the estimated models. These assumptions include normal distribution of residuals, constant variance of the residuals, and no autocorrelation among residuals. The assumptions are commonly tested, when evaluating the reliability of a linear regression model. Moreover, multicollinearity of the of the independent variables is examined. Although only perfect multicollinearity is against Gauss-Markov assumptions, strong multicollinearity is problematic for result interpretation. (Nirmal Ravi Kumar 2020, 211–218.)

The normality assumption of the residuals is not essential for the optimality of the coefficient estimates but it affects the results of the significance tests. However, if the sample is large, the violation of the normality assumption is considered acceptable. (Nirmal Ravi Kumar 2020, 216.) Therefore, normality tests for the model residuals are conducted in this thesis only for the WLS regressions, where the sample size is very small. Weighted residuals of the models are tested with Jarque-Bera test with the null hypothesis that the errors are normally distributed (Taeger – Kuhnt 2014, 150–152).

The assumption of constant error variance, which is also referred to as homoskedasticity of the residuals, is important for the calculation of the standard errors of the coefficients. In section 5.2.6 it was explained that standard errors are used to calculate t-statistics for t-tests. If residuals are heteroskedastic, the standard errors are biased, and the p-values of the t-tests are not reliable. (Nirmal Ravi Kumar 2020, 213–215.) To test for homoskedasticity in time series regressions and OLS regressions, Koenker test is used, as it is less sensitive to the possible non-normality of the residuals in small samples than the commonly used Breusch-Pagan test. The null hypothesis of the test is that the variance of the residuals is homoscedastic (Nirmal Ravi Kumar 2020, 636–642). If model residuals are heteroskedastic, heteroskedasticity-robust White’s standard errors are used to calculate the unbiased t-statistics and heteroscedasticity-robust Wald statistic is used instead of F-test (Nirmal Ravi Kumar 2020, 670–673).

When it comes to the WLS regression models of the thesis, WLS technique is a common method for correcting heteroskedasticity of OLS regressions. The weights of the WLS model are determined to minimize the heteroskedasticity of the residuals. However, the weights in the context of this thesis are equal to the number of stocks in each group similarly to Seyhun (1990). These weights eliminate heteroskedasticity only if the grouped model is homoscedastic at the individual level. (Wooldridge 2020, 277–278.)

As homoskedasticity at the individual level cannot be assumed, the heteroskedasticity of the WLS models' residuals is tested. Following the example of Wooldrigde (2020, 291), the heteroskedasticity of the weighted residuals is tested using the special case of White heteroskedasticity test, where squared weighted residuals are regressed against weighted fitted values and squared weighted fitted values of the model. The null hypothesis of the test is that the variance of the residuals is homoscedastic.

Autocorrelation of the residuals is examined for the estimated time series regression models. Ljung-Box test is used for testing, because it produces reliable results with all sample sizes (Nirmal Ravi Kumar 2020, 642). Null hypothesis of the Ljung-Box test is that there is no autocorrelation in the residuals up to the chosen number of lags (Nirmal Ravi Kumar 2020, 748). If significant autocorrelation is found from the residuals, lagged values of the insider trading variables are added to the time series regression model to reduce it similarly to Seyhun (1990).

Lastly, multicollinearity in the models with multiple independent variables is examined. Multicollinearity means that independent variables of the model have a strong linear relationship. It is problematic when regression model is estimated to understand the relationship between various independent variables and the dependent variable. (Nirmal Ravi Kumar 2020, 516.) To detect multicollinearity, Pearson correlation matrices and variance inflation factors (VIF) are examined. Multicollinearity should not be a problem when correlations are below 0.80 and VIF values are below 10. (Nirmal Ravi Kumar 2020, 537–542.)

5.3.2 Event study robustness

There are multiple factors that affect the robustness of the event study results. The idea of event studies is to measure the effect of an event on the stock price of a company, which raises two questions. How do we know which part of the reaction was caused by the event, and more importantly, how do we know it was caused by that specific event.

Starting with the first question, joint hypothesis problem is inevitable in event studies. The reliability of the results depends on the chosen model for predicting normal returns. The abnormal returns in this thesis are calculated using the market model and Dimson adjusted market model for infrequently traded stocks. This approach provides robustness against thin trading, which according to Dimson and Marsh (1983, 780) causes serious bias in risk measures. However, as a robustness check, the results of the OLS regressions are also estimated using CARs, which have been calculated with the standard market model for all stocks.

There are many models for predicting normal returns, but only market model is used in this thesis. MacKinlay (1997, 19) concludes that more sophisticated multifactor models for predicting normal returns, which have been constructed under the Arbitrage Pricing Theory, offer only small gains compared to market model. This justifies the focus on only one model. However, even when using one model, the length of estimation period and the proxy for the market portfolio influence the results. Vaihekoski (2016) demonstrates how the beta values vary when using different market indices. In addition, the stock market crash of 2020 affects the beta estimates of some events.

The length of estimation period cannot be increased from 160 days due to the limitations of the data. Oma Säästöpankki Oyj was listed on the main list of Nasdaq Helsinki only at the end 2018, and the first insider trades took place in the fall of 2019. However, as a robustness check, CARs are calculated using the stock market index OMXH25 as the proxy for market portfolio instead of OMXHPI. No Dimson adjustments are made for these CARs.

MacKinlay (1997, 35) also states that the incorrect identification of the event day might be an issue in the event studies. If the event window starts from the wrong day, the reaction is not captured in CAR. In insider trading literature, there are studies that have used the transaction date or the notification date as the event day. In this thesis the transaction date is used. As the primary focus of the thesis is to understand how profitable the insider trades were during COVID–19, and not to approximate the signal value of insider trade announcements, the actual trade day is viewed as the most appropriate choice. Moreover, because the insiders are required to publicly disclose their trades within three days after the transaction, 21-day event window should capture this reaction even when transaction date is used. In the sample data, the average lag between transaction date and reporting date is around 4.8 calendar days, but when the most extreme outliers are cleared from the data, the average is around 2.3 calendar days. Still, as a robustness check, CARs are also calculated using the notification date as the event day. OMXHPI is used as a proxy for the market portfolio and no Dimson adjustments are made for these CARs.

Regarding the second question, whether the observed abnormal returns are due to the events in question, the answer is that there is no way of knowing. There might have been some simultaneous event before, during or after the insider trade, which has pushed the return during the event window to abnormal levels. This becomes increasingly likely when the length of the event window increases. However, due to the 30-day closed period of insiders, at least earnings announcements should not affect the returns during the event windows. This should be true, even though closed periods are calculated in calendar days and the length of the event window is defined in trading days.

On the other hand, the uncertainty concerning the underlying reason behind the price reaction might not be as major of a problem in this study than in studies focusing solely on the signal values of the events. The event study methodology is used in this thesis to estimate the short-term risk adjusted profitability of the insider trades. Whether the abnormal returns after the trade are due to the signal value of the trade itself, superior information of the insider, some other simultaneous event, or general market trend is irrelevant when answering the main question of whether COVID–19 affected the profitability. However, when analysing the possible reasons for the returns, this limitation is considered.

Lastly, MacKinlay (1997, 27) raises the issue of event clustering in event studies which use aggregated abnormal returns. He argues that when the event windows of two events overlap, covariances of the event CARs are no longer zero, which affects the reliability of the significance tests. Moreover, Betzer and Theissen (2009, 415) describe how overlapping event windows lead to the contamination of CARs when multiple events happen during one event window.

The problem can be illustrated with a simple example. If insider A purchases shares of firm X on trading day 1 and insider B purchases shares of firm X on trading day 2, the 21-day event windows overlap for 20 days. As the CARs of the events are calculated using almost all the same daily abnormal returns, they are no longer independent from each other. Moreover, the CAR associated with A's trade captures also the market reaction to B's trade and the individual effects of the two events cannot be distinguished.

Fidrmuc et al. (2006, 2971) argue that event clustering is not a problem in their study as the number of purchases and sales for an individual company per year is low, 2.86 and 2.77 respectively. In the sample of this thesis the values are similar, 2.88 for purchases and 2.23 for sales. However, to ensure that event clustering is not a severe problem in the sample, the total number of overlapping event windows are calculated. From the 1229 total events, excluding the companies with negative price-to-book ratios, 1023 have an overlapping event window with another event from the same company. In addition, 339 events have an identical event window with another event.

The results suggest that even when the average number of trades for a company per year is low, the event clustering can influence majority of the transactions. To evaluate the robustness of the results against clustering, two approaches are applied. Firstly, similarly to Van Geyt et al. (2013, 365), all the transactions with overlapping event windows are excluded from the data. This means that no events, which are either happening during the event window of another event or have other events happening in their own event window, are included. After the limitations, the final robustness sample consists of 206 transactions with 69 disposals and 78 trades during the crisis period.

The issue with the first approach is that in addition to decreasing the sample size substantially, it fully excludes all the clusters of trades even though not all of the event windows are contaminated. Thus, the approach of Betzer and Theissen (2009, 416) is also applied, where overlapping events are considered to form a series. The last transaction of the series can be included to the robust sample with the fully independent events, because although it is happening in the event window of the previous event, there are no events during its own window. For the events with exactly the same event window, only one of them is included in the sample. Moreover, unlike in the first approach the filtering of events is done separately for purchases and sales. The final robustness sample consists of 509 transactions with 197 sales and 235 trades during the crisis period.

All in all, five different approaches for examining the robustness of the event study results are used in the thesis. These include market model estimations for CAR without Dimson adjustment, with OMXH25 as the proxy for the market portfolio, and with notification date as the event day. Event clustering robustness is checked with a sample of fully independent events and with a sample where the last event of an event cluster is also considered. These robustness test samples are further referred to as “NoDim”, “OMXH25”, “RepDay”, “EvClu1”, and “EvClu2”, respectively.

6 Results and discussions

6.1 Insider response to the stock market crash of 2020

6.1.1 Descriptive statistics

To understand the response of insiders to the stock market crash of 2020 the changes in their trading measures and ratios are illustrated with figures and tables. Figures 5, 6, and 7 present the changes in insider trading from 2019 to 2021. In Figure 5 *NP* denotes to number of purchases, *NS* denotes to number of sales, and *PRAT* is their ratio. In Figure 6 *SP* denotes to shares purchased, *SS* denotes to shares sold, and *SPRAT* is their ratio. In Figure 7 *EP* denotes to euros purchased, *ES* denotes to euros sold, and *EPRAT* is their ratio.

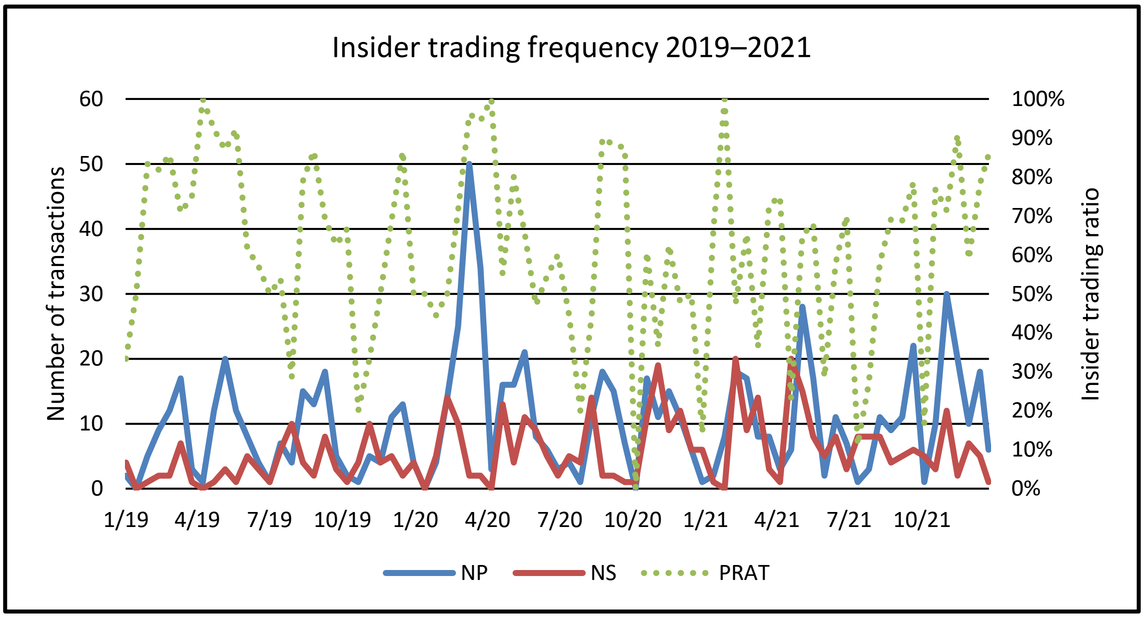

Figure 5. Insider trading frequency 2019–2021.

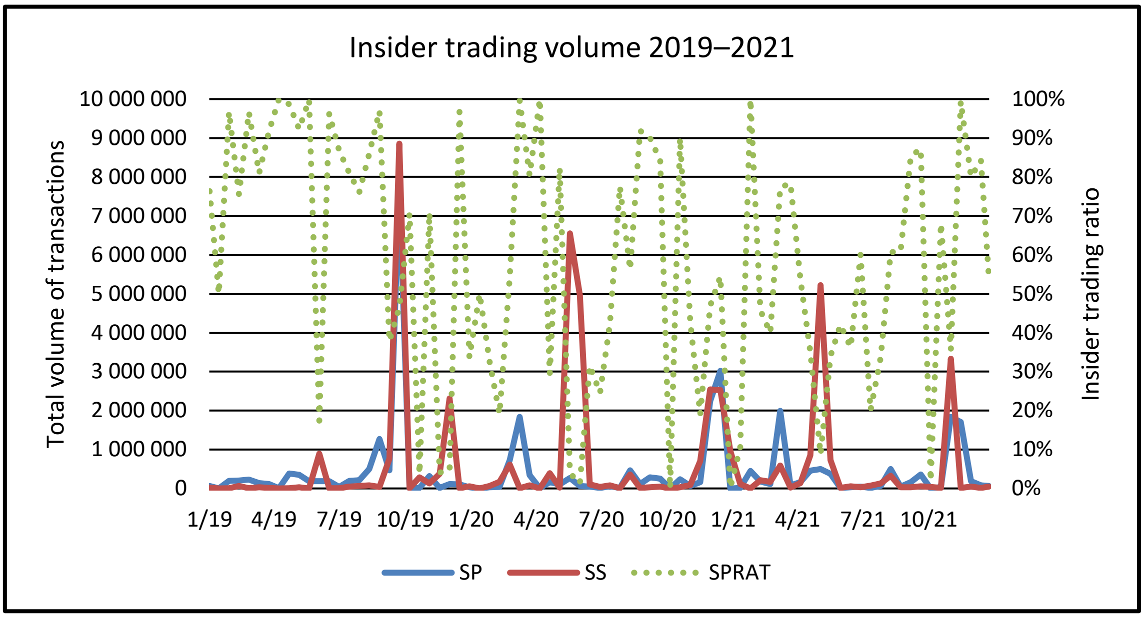

Figure 6. Insider trading volume 2019–2021.

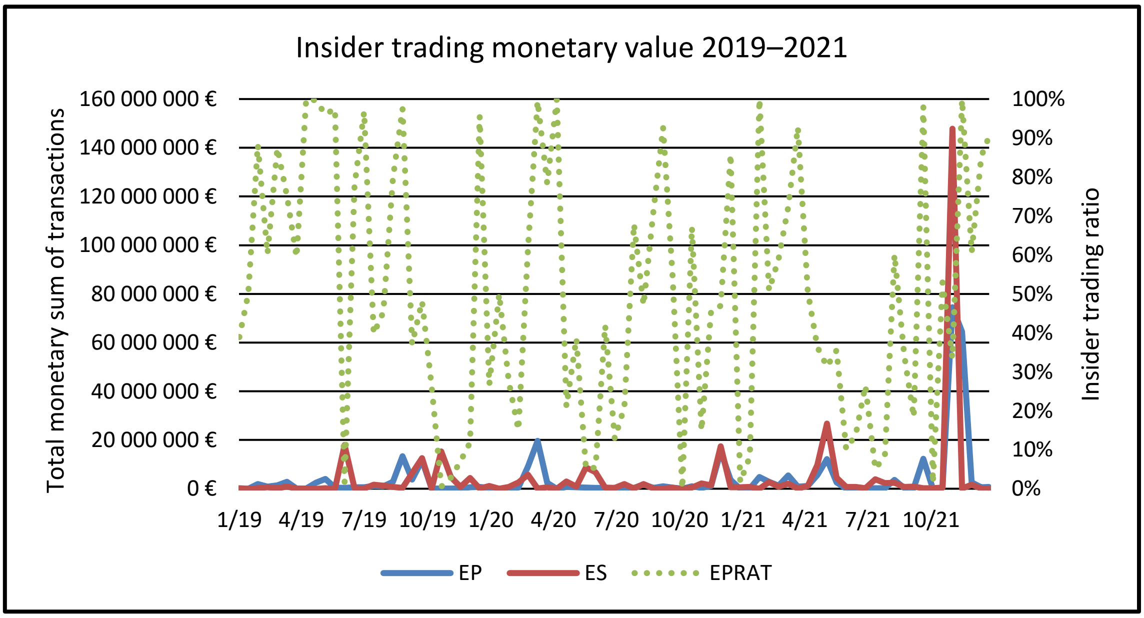

Figure 7. Insider trading monetary value 2019–2021.

Firstly, Figure 5 indicates that there was a clear peak in the number of insider purchases around the stock market crash of 2020. This seems to suggest that insiders viewed the crash as a lucrative purchase opportunity. No similar irregularities are seen for insider sales. In addition, *PRAT* appears to be a volatile ratio as the share of purchases change quickly in two-week periods. However, it indicates that around March of 2020 the insiders were primarily purchasing.

Secondly, Figure 6 shows, that there are several peaks in shares purchased and shares sold during the sample period. Some of these peaks can be explained by single transactions.

For instance, on September 30, 2019, over 7 million shares of SRV Yhtiöt Oyj were traded from one insider to another. As both purchase volumes and sales volumes peaked, *SPRAT* wasn't affected by the trade. Supporting the earlier indication of high purchase activity around the crash of 2020, there is a moderate peak in shares purchased around the March of 2020. Similarly to *PRAT*, also *SPRAT* seems to be a volatile ratio. It indicates that insiders were mainly buying shares during the stock market crash. However, this seems to have been the case also during the first months of 2019 and 2021.

Thirdly, Figure 7 also supports the increased purchasing by insiders during the March of 2020 as insiders purchased shares in aggregate with approximately 20 million euros during a single two-week period. *EPRAT* peaks also during the crash and it seems to behave very similarly to *SPRAT* during the sample period. However, Figure 7 is mostly dominated by the significant sales and purchase peaks in the end of 2021. Further investigation reveals that the peaks are caused by the trades of former CEO and Chairman of the Board of Sampo Oyj Björn Wahlroos.

Based on the Figures 5, 6, and 7, there are indications of increased purchasing activity during the crash of 2020. Thus, a more detailed view on the trading measures is presented in a form of tables. Table 3, Panel A, presents the biweekly insider trading variables around the stock market crash. Panel B shows key biweekly statistics for the total sample period from 2019 to 2021. The figures from the crash period, weeks 7 to 12, are bolded, while weeks 1 to 6 represent the pre-crash period, and weeks 13 to 18 are the post-crash period.

Table 3. Biweekly insider trading variables around market crash of 2020.

NP is the number of purchases and *NS* is the numbers of sales. *SP* is the number of shares purchased and *SS* is the numbers of shares sold. *EP* is euros purchased and *ES* is euros sold.

PANEL A: Biweekly insider trading variables around market crash 2020						
Time period	**NP**	**NS**	**SP**	**SS**	**EP**	**ES**
Week 1–2, 2020	4	4	28,322	55,822	€399,831	€1,097,878
Week 3–4, 2020	0	0	0	0	€0	€0
Week 5–6, 2020	4	5	30,966	64,196	€283,388	€746,758
Week 7–8, 2020	**14**	**14**	**39,741**	**168,228**	**€454,232**	**€2,555,586**
Week 9–10, 2020	**25**	**10**	**728,073**	**609,600**	**€9,164,882**	**€5,683,299**
Week 11–12, 2020	**50**	**2**	**1,837,786**	**6,000**	**€19,685,285**	**€102,540**
Week 13–14, 2020	34	2	339,546	83,046	€2,423,856	€671,281
Week 15–16, 2020	3	0	3,429	0	€16,332	€0
Week 17–18, 2020	16	13	162,731	391,589	€787,322	€2,954,681
PANEL B: Biweekly sample statistics 2019–2021						
Mean	10.3	5.6	420,392	591,486	€3,914,346	€4,288,401
SD	8.7	4.8	997,207	1,511,352	€11,264,989	€16,903,163
Min	0	0	0	0	€0	€0
Max	50	20	7,704,826	8,854,336	€74,513,220	€147,818,176

Table 3 indicates that all insider purchase measures peaked during the last two weeks of the crash period. The measures were substantially above the average levels, and the number of purchases even reached its highest value during the crash when considering the total sample period from 2019 to 2021. During the same weeks, sales measures were below the average levels. On the other hand, during the pre-crash period, all the insider trading measures including purchases and sales were below average levels.

Similarly, Table 4, Panel A, presents the biweekly insider trading ratios around the stock market crash, and Panel B shows key biweekly statistics for the total sample period from 2019 to 2021.

Table 4. Biweekly insider trading ratios around market crash of 2020.

PRAT is calculated as *NP*/(*NP*+*NS*), *SPRAT* is calculated as *SP*/(*SP*+*SS*), and *EPRAT* equals *EP*/(*EP*+*ES*).

PANEL A: Biweekly insider trading ratios around market crash 2020			
Time period	**PRAT**	**SPRAT**	**EPRAT**
Week 1–2, 2020	50.0%	33.7%	26.7%
Week 3–4, 2020	50.0%	50.0%	50.0%
Week 5–6, 2020	44.4%	32.5%	27.5%
Week 7–8, 2020	**50.0%**	**19.1%**	**15.1%**
Week 9–10, 2020	**71.4%**	**54.4%**	**61.7%**
Week 11–12, 2020	**96.2%**	**99.7%**	**99.5%**
Week 13–14, 2020	94.4%	80.3%	78.3%
Week 15–16, 2020	100.0%	100.0%	100.0%
Week 17–18, 2020	55.2%	29.4%	21.0%
PANEL B: Biweekly sample statistics 2019–2021			
Mean	61.5%	57.8%	50.0%
SD	23.2%	31.6%	32.7%
Min	0,0%	0.0%	0.0%
Max	100,0%	100.0%	100.0%

Table 4 shows that all insider trading ratios increased towards the end of the crash period. In other words, most of the insider trades during weeks 11 and 12 were purchases, the majority of the shares traded were purchased, and the majority of the money involved was used to purchase shares. This indicates that insiders viewed the last weeks of the crash as a good opportunity to acquire shares and seem to not have been extremely concerned about the effects of COVID-19. However, a regression analysis is needed to verify this conclusion.

Regarding the timing of the insider trades during the 2020 crash, closed periods are an important factor to consider. As mentioned in section 2.2.2, insiders are prohibited to trade 30 days prior to the release of financial statements. As most companies have aligned their fiscal year with calendar year, they release annual reports and quarterly results of the first quarter during springtime. Figure 8 illustrates the changes in the percentage of companies in the sample under closed period during the spring of 2020. The release dates for quarterly results and annual reports have been collected from the Central Storage Facility of Nasdaq (Nasdaq Central Storage Facility).

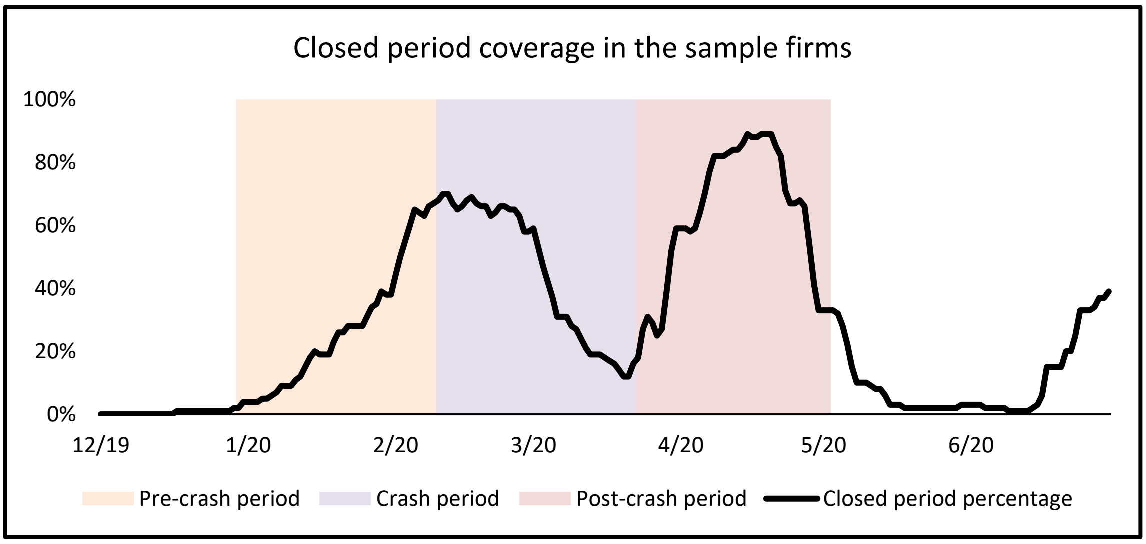

Figure 8. Closed period coverage (Nasdaq Central Storage Facility).

According to Figure 8, there were two peaks during the spring of 2020, where around 70% and 90% of sample companies were under closed periods. The first peak was mostly caused by the releases of annual reports from 2019 and the second one was due to the release of quarterly reports for the first quarter of 2020. Between the peaks in the second half of March, the number of companies under closed periods was close to 10%.

Earlier, the insider trading measures indicated that the trading activity increased towards the end of the crash. The highest activity was found during the weeks 11 and 12, which cover the period from 9/3/2020 to 22/3/2020. This is also the period, when closed period coverage was the lowest based on Figure 8. Therefore, the timing of the insider trades during the 2020 crash might not only be due to superior information but also regulatory constraints. Some insiders might have been willing to respond already earlier but were not allowed to.

6.1.2 Time series regression analysis and result robustness

The statistical significance of the changes in insider trading activity before, during, and after the crash is examined with time series regression models. Table 5 presents the results of the biweekly time series regression models for each of the nine insider trading variables. Results for model residual tests including Koenker test for heteroskedasticity and Ljung-Box test for autocorrelation up to 20 lags are also included in Table 5.

Table 5. Time series regressions of biweekly insider trading 2019–2021.

D₁ is the dummy variable for the pre-crash period from 30/12/2019 to 9/2/2020. D_2 is the dummy variable for the crash period from 10/2/2020 to 22/3/2020. D_3 is the dummy variable for the post-crash period from 23/3/2020 to 2/5/2020. K refers to the p-value of the Koenker test for heteroskedasticity of the model residuals. LB refers to the p-value of the Ljung-Box test for autocorrelation of the model residuals up to 20 lags. *NP* is the number of purchases and *NS* is the numbers of sales. *SP* is the number of shares purchased and *SS* is the numbers of shares sold. *EP* is euros purchased and *ES* is euros sold. *PRAT* is calculated as *NP*/(*NP*+*NS*), *SPRAT* is calculated as *SP*/(*SP*+*SS*), and *EPRAT* equals *EP*/(*EP*+*ES*). P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample size is 79 in all regressions.

Time series regression models of biweekly insider trading 2019–2021							
		Regression model				**Residuals**	
#	**Trading Variable**	**Constant**	**D_1**	**D_2**	**D_3**	**K**	**LB**
1	NP	9.46	–6.79	20.21	8.21		
		(**0.00**)	(0.14)	(**0.00**)	(0.08)	(**0.00**)	(**0.01**)
2	NS	5.63	–2.63	3.04	–0,63		
		(**0.00**)	(0.36)	(0.29)	(0.83)	(0.84)	(**0.00**)
3	PRAT	0.61	–0.13	0.12	0.23		
		(**0.00**)	(0.36)	(0.39)	(0.10)	(0.54)	(0.99)
4	SP	429,148	–409,385	439,385	–260,579		
		(**0.00**)	(0.50)	(0.47)	(0.66)	(0.98)	(1.00)
5	SS	647,842	–607,836	–386,566	–489,630		
		(**0.00**)	(0.51)	(0.67)	(0.59)	(0.89)	(0.76)
6	SPRAT	0.58	–0.19	–0.00	0.12		
		(**0.00**)	(0.31)	(0.99)	(0.54)	(0.38)	(0.34)
7	EP	3,943,118	–3,715,378	5,825,015	–2,867,281		
		(**0.01**)	(0.58)	(0.39)	(0.67)	(0.97)	(0.59)
8	ES	4,642,452	–4,027,573	–1,861,977	–3,433,798		
		(**0.03**)	(0.69)	(0.86)	(0.74)	(0.98)	(1.00)
9	EPRAT	0.50	–0.15	0.09	0.17		
		(**0.00**)	(0.45)	(0.64)	(0.39)	(0.35)	(0.73)

The results in Table 5 show that the constants of all nine regression models are significantly different from zero. In other words, there was significant insider trading activity different from zero during the period from 2019 to 2021. When it comes to the changes in insider trading before, during and after the stock market crash of 2020, only the crash period coefficient for *NP* is significant. There were approximately 20 insider purchases more in the two-week periods during the crash than normally.

However, the residual tests reveal that the results of the Models 1 and 2 in Table 5 are not robust. The null hypothesis of the Koenker test suggesting residual homoskedasticity can be rejected for Model 1. Moreover, the Ljung-Box test suggests that the residuals of both Models 1 and 2 autocorrelated. Therefore, these models are respecified and re-estimated. To alleviate the autocorrelation of the residuals, lagged values of the insider trading variable are added to the regression equation. The lags used in the error model are specified by visually exploring the autocorrelation function plots. In addition, heteroskedasticity-robust White's standard errors are used for Model 1 to calculate robust p-values for the coefficients. The results of the new estimations are presented in Table 6.

Table 6. Robust regression models of biweekly insider trading 2019–2021.

D_1 is the dummy variable for the pre-crash period from 30/12/2019 to 9/2/2020. D_2 is the dummy variable for the crash period from 10/2/2020 to 22/3/2020. D_3 is the dummy variable for the post-crash period from 23/3/2020 to 2/5/2020. LB refers to the p-value of the Ljung-Box test for autocorrelation of the model residuals up to 20 lags. *NP* is the number of purchases and *NS* is the numbers of sales. *Lag1*, *Lag2*, and *Lag6* are the lagged values of the dependent insider trading variables. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample sizes are 77 for Model 1 and 73 for Model 2.

Robust regression models of biweekly insider trading 2019–2021									
		Regression model				**Error model**			**Residuals**
#	**Trading Variable**	**Constant**	**D_1**	**D_2**	**D_3**	**Lag1**	**Lag2**	**Lag6**	**LB**
1	NP	8.57	–5.42	17.10	8.17	0.40	–0.30	–	
		(**0.00**)	(**0.00**)	(**0.03**)	(0.15)	(**0.00**)	(**0.01**)	–	(0.55)
2	NS	3.95	–2.34	3.04	0.21	0.08	–	0.25	
		(**0.00**)	(0.42)	(0.30)	(0.94)	(0.52)	–	(**0.04**)	(0.14)

Table 6 indicates, that after adding the error models to the regressions, both Models 1 and 2 are consistent with the assumption of non-autocorrelation of the residuals. All coefficients of Model 2 remain insignificant. However, for Model 1 both pre-crash period and crash period coefficients are statistically significant at 5% level. The number of insider purchases was around three acquisitions per two weeks during the pre-crash period, which is significantly less than normally. During the crash period insiders made almost 26 purchases per two weeks. The results suggest that insiders were cautious in their purchases before the stock market crash of 2020 and responded to the crash with increased buying.

6.1.3 Discussion

Majority of the insider trading variables did not show statistically significant changes around the stock market crash of 2020. There were no changes in purchase ratios measured with number of transactions, aggregated stock volumes or aggregated monetary values. However, there was significant changes in the number of insider purchases during the spring of 2020. During the six weeks before the crash, there was significantly less insider purchases than normally. Moreover, during the crash period, the number of purchases was significantly higher. What do these results imply?

Firstly, the decrease in insider purchasing indicates that insiders were cautious in their trading during the first six weeks of 2020. During those weeks COVID-19 started to spread from China to other countries and gained attention in the media. The uncertainty created by the virus seems to have affected insiders' behaviour. On the other hand, there was no significant changes in the number of insider sales during the pre-crash period, which supports the view that insider didn't foresee the crash. Therefore, it seems that insiders didn't have a clear understanding of the effects of the virus early on and decided to observe the situation instead of heavy trading. This view is also supported by the fact, that total number of purchases and sales was below average during the pre-crash period.

Secondly, the increase in insider purchasing during the crash period suggests that insiders did not perceive the effects of COVID-19 as detrimental to their businesses than other investors. As insiders have the best knowledge about their firms and were willing to purchase shares in aggregate, the steep decrease in stock prices may not have been fully justified by a major change in underlying fundamentals. Instead, insider trading behaviour indicates that similarly to the results of Seyhun (1998, 143–145) from 1987 crash, outside investors were overreacting to the COVID-19 news and selling their shares irrationally.

On the other hand, the impact of signalling to these results should not be overlooked. In section 3.4 it was described how management might be tempted to use insider trading as a way to signal confidence in their firm even when the future is very uncertain. Because stock prices were on a free fall during the March of 2020, part of the insider purchase peak might be explained by the management's desire to restore the public trust to their firm rather than solely making money. At the market level, the crash ended after only 6 weeks, so if insider trades were indeed used for signalling purposes, it appears that they were rather successful judging by the outcome.

Lastly, the timing of the insider trades within the crash period, which was concentrated on the last two weeks, might be partly explained by the high number of firms under closed trading periods during the first weeks of the crash. Insiders in aggregate seem to have been fortunate to not be allowed to trade before the prices reached the bottom. The other explanation is that insiders had superior information regarding the end of the crash or that they started to signal only after a major decline in prices, but it would be quite a coincidence that their views would be so well aligned with their regulatory constraints. Whether insiders truly understood and predicted the effects of the pandemic better than outsiders or were just signalling is a question, that can only be answered when examining the post-crash returns of the stocks traded during the crash. The next section assesses this question.

6.2 Post-crash performance of stocks traded by the insiders

6.2.1 Descriptive statistics

Following the methods described in 5.2.3, the stocks in the insider trading data are organized into nine groups for WLS regressions. Table 7 presents the key statistics for the groups.

Table 7. Descriptive statistics: WLS regression groups.

Average market capitalization of the group is presented in million euros, P/B refers to average price-to-book ratio of the group, β is the average risk measure for the group, R_c refers to average crash returns of the group, R_{pc} is the average 6-month post-crash return of the group, and Obs. is the number of observations on each group.

Descriptive statistics: WLS regression groups						
Group	**Market Cap (M€)**	**P/B**	**β**	**R_c (%)**	**R_{pc} 6 mo. (%)**	**Obs.**
Large Cap & High P/B	8,741.67	5.10	0.70	–26.31%	53.36%	11
Large Cap & Mid P/B	7,671.06	1.79	1.06	–32.90%	38.11%	12
Large Cap & Low P/B	10,372.86	0.92	1.23	–40.32%	23.84%	5
Mid Cap & High P/B	499.39	6.62	0.42	–28.05%	46.80%	16
Mid Cap & Mid P/B	412.86	2.07	0.44	–30.10%	35.06%	11
Mid Cap & Low P/B	445.49	0.99	0.30	–26.94%	11.09%	8
Small Cap & High P/B	61.37	5.02	0.32	–36.87%	77.08%	5
Small Cap & Mid P/B	61.10	1.77	0.35	–30.45%	16.15%	10
Small Cap & Low P/B	61.08	0.89	0.35	–27.17%	16.94%	20
Weighted average	**2,635.82**	**2.85**	**0.54**	**–29.73%**	**33.39%**	

Based on Table 7, stocks of all sizes and valuations experienced large negative returns during the stock market crash of 2020 and major positive returns during the six months following the crash. However, it seems that the post-crash increases were bigger for growth stocks with high price-to-book ratios independent from the size of the company.

In addition, it seems that betas of especially the Mid and Small Cap company groups are low. The average beta for stocks in the market should be equal to 1 (Vaihekoski, 2016).

In this sample, it is 0.54. This indicates that either insiders of high-risk companies do not trade as much, or that the beta estimations in the sample might be inaccurate. As low betas appear to be associated with smaller companies, which typically experience infrequent trading, the latter explanation seems more plausible. Thin trading is known to influence beta estimations, and Vaihekoski (2016) argues that it leads to lower betas. Following the methodology of Seyhun (1990), thin trading adjustments were not made for the estimates in this research question, which appears to be a reasonable explanation for the low betas. At the same time, it demonstrates the importance of the thin trading adjustments in the event study phase of the thesis.

6.2.2 WLS regression analysis and result robustness

As insiders seemed to view the stock market crash of 2020 as a lucrative opportunity to acquire shares or at least sent such signals, the natural follow-up question is whether the trades they made during the crash were successful. Table 8 presents the results for the estimated WLS regressions, where the six-month post-crash returns are explained by the changes in different insider trading ratios during the crash. Crash returns, beta estimates, natural logarithm of market capitalizations, and price-to-book ratios are added to the regression as control variables to ensure, that insiders' returns are not driven by the contrarian anomaly, higher risk level of the investments, size anomaly, or value anomaly.

Table 8. WLS regression: 6-month returns.

The dependent variable is the 6-month post-crash return. The independent variables are the change in insider trading ratios *PRAT*, *SPRAT*, and *EPRAT*, crash returns R_c, risk measure β, natural logarithm of market capitalization *MC*, and price-to-book ratio *PB*. Model diagnostics include the Jarque-Bera test for normality, the special case of White test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample size is 9 in all regressions.

Weighted least squares regression: 6-month post-crash returns			
	Model 1 (ΔPRAT)	**Model 2 (ΔSPRAT)**	**Model 3 (ΔEPRAT)**
Constant	–1.20	–0.56	–0.65
	(0.24)	(0.57)	(0.42)
ΔInsider trading variable	0.11	0.09	0.11
	(0.06)	(0.08)	(**0.04**)
R_c	–2.30	–2.02	-2.02
	(0.12)	(0.18)	(0.11)
β	–0.33	–0.08	–0.08
	(0.35)	(0.81)	(0.78)
MC	0.04	0.01	0.01
	(0.36)	(0.89)	(0.83)
PB	0.05	0.06	0.07
	(**0.04**)	(**0.03**)	(**0.01**)
Multiple R-squared	0.94	0.93	0.95
Adjusted R-squared	0.84	0.81	0.88
F-test: p-value	(**0.05**)	(0.06)	(**0.03**)
Model diagnostics			
Jarque-Bera: p-value	(0.78)	(0.70)	(0.66)
White test: p-value	(0.35)	(0.89)	(0.41)
Correlation matrix (max)	0.86	0.86	0.86
VIF (max)	11.84	11.24	11.25

Table 8 indicates that the changes insider purchasing ratios during the crash of 2020 seem to explain part of variability in post-crash returns. The coefficient for *ΔEPRAT* is significant at 5% level, and coefficients for *ΔPRAT*, and *ΔSPRAT* are significant at 10% level. As the sample size is very small, 10% significance level is appropriate. Coefficients of all models for the change in insider trading variable are positive, which means that the stocks that insiders bought (sold) more than normally during the crash showed larger (smaller) returns after six months. Considering that insiders were mostly purchasing shares during the crash, the results imply that they were able to identify undervaluations in their companies during the crash. The better returns are not explained by higher risk level or other well-known anomalies, as these effects were controlled for.

When it comes to the control variables, only the price-to-book ratios from the end of 2019 are able to statistically significantly explain the post-crash returns. This seems logical after analysing the group-level descriptive statistics of Table 7. The coefficients for P/B ratios are positive for all models, which indicates that higher price-to-book ratios are associated with the higher post-crash returns. In other words, growth stocks recovered better from the crash. The result contradicts with the traditional value effect, which suggest that low price-to-book companies deliver abnormal returns.

F-test results show that overall Models 1 and 3 are statistically significant, whereas Model 2 is only significant on 10% significance level. The R-squared values, which indicate how much of the variation in the dependent variable the model can explain, are very high for all models, even when adjusted for the number of variables. As only a few of the independent coefficients are significant, this might indicate multicollinearity problems (Nirmal Ravi Kumar 2020, 534). Model diagnostics in Table 8 reveal that there is multicollinearity between the independent variables. The highest VIF values are over 11 and highest correlations over 0.8. The full correlation matrix between the independent variables and all VIF values can be seen in Appendix 1. They show that the independent variables causing multicollinearity problems are beta (β) and market capitalization (MC). Knowing that betas of small companies were generally lower due to thin trading, this result is expected.

Regarding the other model diagnostics in Table 8, the residuals of all models are normal, as the null hypothesis of the Jarque-Bera test cannot be rejected. Similarly, all p-values from the White tests exceed the 5% significance level. This suggests that the null hypothesis of residual homoscedasticity cannot be rejected, and regular standard errors should be appropriate in the t-tests. However, the very small sample size might influence the results of the robustness checks.

To examine the effect of the chosen post-crash return period to the results, Table 9 presents the WLS regressions where the dependent variable is the 12-month post-crash return.

Table 9. WLS regression: 12-month returns.

The dependent variable is the 12-month post-crash return. The independent variables are the change in insider trading ratios *PRAT*, *SPRAT*, and *EPRAT*, crash returns R_c, risk measure β, natural logarithm of market capitalization *MC*, and price-to-book ratio *PB*. Model diagnostics include the Jarque-Bera test for normality, the special case of White test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample size is 9 in all regressions.

Weighted least squares regression: 12-month post-crash returns			
	Model 1 (ΔPRAT)	**Model 2 (ΔSPRAT)**	**Model 3 (ΔEPRAT)**
Constant	4.03	4.41	4.21
	(0.12)	(0.06)	(0.11)
ΔInsider trading variable	0.04	0.08	0.02
	(0.66)	(0.27)	(0.81)
R_c	0.73	0.75	0.87
	(0.79)	(0.73)	(0.75)
β	0.91	1.03	1.00
	(0.28)	(0.16)	(0.24)
MC	–0.19	–0.21	–0.20
	(0.11)	(0.06)	(0.11)
PB	0.11	0.11	0.12
	(**0.05**)	(**0.02**)	(**0.04**)
Multiple R-squared	0.84	0.89	0.83
Adjusted R-squared	0.57	0.71	0.54
F-test: p-value	(0.19)	(0.11)	(0.20)
Model diagnostics			
Jarque-Bera: p-value	(0.56)	(0.67)	(0.41)
White test: p-value	(0.64)	(0.56)	(0.57)
Correlation matrix (max)	0.86	0.86	0.86
VIF (max)	11.84	11.24	11.25

Table 9 shows that with longer post-crash return period, the coefficients for the changes in insider trading variables during the crash of 2020 are no longer significant. In other words, insiders were not able to identify undervalued companies during the crash when looking at the cumulative returns from the year after the crash ended. This challenges the interpretation of the earlier results presented in Table 8, which suggested that insiders detect undervaluation statistically significantly. It seems that this is only true when looking at the short-term returns of six months.

When it comes to the control variables, coefficients for crash returns, beta, and market capitalization have all changed from positive to negative or vice versa with the longer return period. However, none of these coefficients are significant at 5% level similarly to the results in Table 8. At 10% level, coefficient for *MC* in Model 2 is significant and negative indicating that smaller companies generated higher post-crash returns. The result is consistent with the previous research on size anomaly. The coefficients for price-to-book ratios remain positive and significant. Even with longer return period, growth stocks have generated better returns than value stocks. For additional information, Appendix 2 shows the WLS regressions for 18-month post-crash returns. These results are similar to the results in Table 9, and except for the price-to-book ratios, there are no significant coefficients in the models.

6.2.3 Discussion

The results of the weighted least squares regressions indicate that insiders were able to identify short-term undervaluations in their companies during the crash of 2020. Seyhun (1990, 1381–1382) reported similar, although more significant, results. Due to the small sample size, 10% significance level was applied in this thesis when interpretating the results. As the risk level of the company and other well-known return anomalies were controlled for, the better returns of companies with increased insider purchasing could be a sign of superior information regarding the effects of COVID-19.

Earlier it was concluded that, insiders viewed the crash as a good opportunity to purchase stocks at least if measured with the number of purchases. The results of WLS regressions suggest that this view was justified, and the steep decrease in stock price for some companies did not seem to be backed by the underlying fundamentals. Moreover, the results suggests that if insider trades during the crash were motivated by signalling purposes, at least in the short-term, the management was not sending false signals.

The significance of the coefficients for the change in insider trading ratios disappears when the length of the return period increases. When looking at the 12-month or 18-month returns, insiders' behaviour couldn't explain the returns. It might be that the initial undervaluation was corrected by the markets during the first few months, and thus the effect was only seen in 6-month returns. After that, the underlying fundamentals really changed and the subsequent returns for insiders' trades were poorer, which explains why insider trading activity isn't indicative of the long-term returns.

On the other hand, it is also likely that the true effects of COVID-19 were only seen after a longer time period than six months. During the first months after the crash, investors might have evaluated the effects of the pandemic by choosing to invest in firms, that were purchased by insiders. This signalling effect might have inflated the returns of stocks purchased by insiders in the short-term. Once the real effects of the pandemic started to affect the stock prices via earnings reports, the initial signalling effect diminished and insiders' stock picking ability during the crash decreased.

The interpretation of the results is very difficult due to the complex nature of stock markets. The explanations presented above are just some of the reasons that could explain the results. It should also be noted, that even if insiders were able to find undervalued stocks during the crash, it doesn't necessarily mean that they were collecting free money from the markets. The competing explanation for irrational outside investors is that there is some form of a risk involved with these stocks that the control variables did not capture.

Lastly, it must be emphasized that the reliability of the results is questionable. Firstly, due to the grouping of the stocks to calculate insider trading ratios, the sample size decreases to very small with only nine groups. This might distort the results of the WLS regression, and the White test for heteroskedasticity. Secondly, the grouping of control variables might drive the results. Especially for the variables R_c and β, which were not used in forming the groups, the individual observations are mixed in the groups and might cancel each other out within a group. Moreover, there seems to be issues in beta estimates due to thin trading. Thirdly, there is serious multicollinearity between the variables, which affects the reliability of multiple regression models negatively. For all these reasons, the results of the WLS regressions must be approached with caution.

6.3 The effect of COVID-19 on the profitability of insider trading

6.3.1 Descriptive statistics

So far, it has been found that the number of insider purchases peaked during the stock market crash of 2020 and that insiders seem to have been able to identify short-term undervaluations in their companies during the crash. However, the uncertainty caused by the COVID-19 was present in the markets also after the crash. If insiders were able to use their superior information during the crash period, did they also have an advantage in the markets throughout the crisis? To answer this question, the effect of the COVID-19 related uncertainty to the short-term profitability of the insider trading is addressed.

Using event study methodology, abnormal returns are estimated for each transaction. The development of cumulative average abnormal return from the event day up to 20 trading days after the event is presented in Figure 9. CAARs for purchases and sales are reported separately. Moreover, CAARs calculated from crisis period, non-crisis period and total sample period are reported. Crisis period is defined as the period from the beginning of 2020 to the end of March 2021.

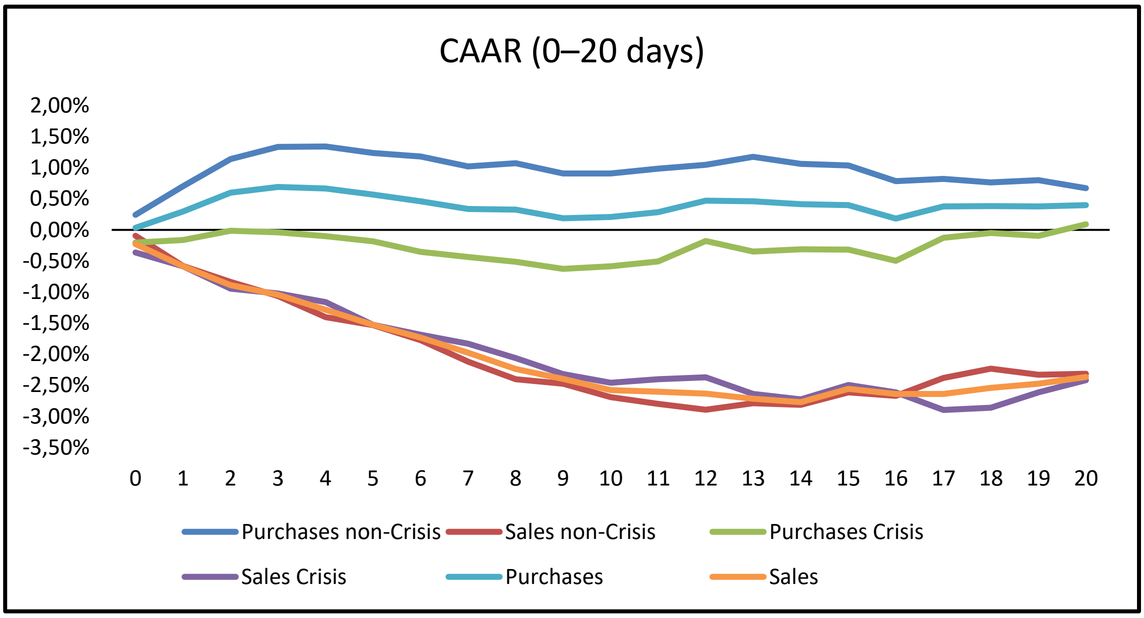

Figure 9. CAAR (0–20 days).

Figure 9 shows that during the whole sample period the CAARs are positive after insider purchases and negative after insider sales. This indicates that insider trades are followed by abnormal returns, and that insiders manage to purchase (sell) before positive (negative) abnormal returns. The positive CAARs after an insider purchase remain at around 0.5% level during the 21-day event window, while the negative CAARs after an insider sale decrease until around fifteenth trading day after the event. Negative CAARs following insider sales are also larger in magnitude than positive abnormal returns after purchases.

When it comes to the effect of COVID-19 crisis, there seems to be almost no difference in CAARs after sales between the crisis period and non-crisis period. However, after purchases, the CAARs are more positive during the non-crisis period. During the crisis period, CAARs following purchases are even negative for most of the days in the event window. This suggests that uncertainty related to COVID-19 might have affected the abnormal returns of insiders by decreasing the returns after purchases. Overall, insider disposals seem to be a more informative signal of the future abnormal returns than purchases.

To get a better understanding of the qualities of the events during crisis and non-crisis periods, the two groups are compared in Table 10. The table presents the results of the t-tests and Mann-Whitney U tests for differences between the mean and median values of the crisis group and the non-crisis group.

Table 10. Descriptive statistics: Non-crisis and crisis period.

The crisis period spans from 1/1/2020 to 31/3/2021. The non-crisis period spans from 1/1/2019 to 31/12/2019, and from 1/4/2021 to 31/12/2021. $CAR_{(0,20)}$ is cumulative abnormal return for all events, $CAR_{(0,20)P}$ for purchases, and $CAR_{(0,20)S}$ for sales. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. *Sales* is a dummy variable for disposals. *CEO*, *CFO*, *MoB*, *OSM*, and *CAP* are the dummy variables for CEOs', CFOs', Board members', other senior managers', and closely associated persons' trades. P-values of t-tests and Mann-Whitney U tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample size for non-crisis group is 642 and for crisis group 587.

Descriptive statistics: Non-crisis and crisis period						
	T-test (mean)			**Mann-Whitney U test (median)**		
	non-crisis	**crisis**		**non-crisis**	**crisis**	
$CAR_{(0,20)}$ (%)	1.24%	0.62%	(0.29)	1.03%	1.65%	(0.85)
$CAR_{(0,20)P}$ (%)	0.66%	–0.45%	(0.14)	0.53%	1.36%	(0.98)
$CAR_{(0,20)S}$ (%)	–2.32%	–2.42%	(0.91)	–2.06%	–2.11%	(0.60)
TS (%)	0.22%	0.09%	(0.14)	0.01%	0.00%	(**0.00**)
MC (B€)	2.48	3.69	(**0.01**)	0.26	0.30	(0.59)
PB	3.70	3.42	(0.28)	2.03	1.97	(0.39)
NoT	3.74	3.96	(0.12)	3	4	(**0.00**)
Lag (days)	3.13	6.72	(**0.01**)	2	2	(0.26)
Sales	0.35	0.37	(0.41)	0	0	(0.41)
CEO	0.08	0.12	(**0.04**)	0	0	(**0.04**)
CFO	0.06	0.08	(0.12)	0	0	(0.12)
MoB	0.25	0.22	(0.38)	0	0	(0.38)
OSM	0.28	0.26	(0.52)	0	0	(0.52)
CAP	0.33	0.32	(0.46)	0	0	(0.46)

Firstly, Table 10 indicates that there are no statistically significant differences between CARs from the crisis and the non-crisis period. The biggest difference between the groups seems to be in CARs after purchases, where the average CAR is positive during the non-crisis period and negative during the crisis period. This finding is supported by the curves in Figure 9 also. Similarly, in absolute numbers, the magnitude of mean CARs is bigger for sales than purchases.

When comparing the mean values and the median values of CARs, the means seem to be higher during the non-crisis period except for sales, while the medians are higher during the crisis period. Especially for purchases, the differences between the periods are noticeable. During non-crisis period, median for purchases is 0.53% and mean is 0.66%, which indicates there are some big returns pushing the mean value up. In the crisis period, the same measures are 1.36% and –0.45% respectively, which means that there must be substantial negative CAR values during the crisis, that lower the mean of the group considerably. However, this result is not surprising when the general market environment during the crisis is considered. As there was over 30% drop in the stock prices during the crash of 2020, all CARs for purchases from that period are probably highly negative. This would explain the large gap between the mean and the median values during the crisis and the effect could possibly be later captured by the dummy variable *Crisis_Q1_20* in regression models.

The t-test results for the control variables suggest that significantly larger companies were traded during the crisis period. Also, the average lag between the transaction date and the notification date is longer during the crisis. Mann-Whitney U test results indicate that the distributions for trade sizes and number of trades per trading day are significantly different in the two periods. Lastly, there are no significant differences between the groups in the share of disposals or share of trades by CFOs, Board member, other senior managers, or closely associated persons. However, the number of trades executed by CEOs is significantly higher during the crisis period. The possible reasons for the higher trading activity of CEOs could be that they either had a bigger information advantage during uncertainty or that they were more willing to signal their trust in the firm in a challenging market environment than other insiders. Considering that CEO's job is most at risk during difficulties, the latter explanation seems plausible.

6.3.2 OLS regression analysis and result robustness

First OLS regressions examine the overall profitability of the insider trading during the sample period. The results are presented in Table 11.

Table 11. OLS regression: Abnormal returns 2019–2021.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Abnormal returns 2019–2021			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	0.94%	0.14%	–2.36%
	(**0.00**)	(0.71)	(**0.00**)
Sample size	1229	787	442

The results in Table 11 suggest that insider trades are associated with statistically significant cumulative abnormal returns of approximately 1% during the 21-day event window in the sample from 2019 to 2021. This finding is consistent with previous research, which has also found abnormal returns for insiders. However, when examining purchases and sales separately, it can be stated that the overall significance of the results is driven by the highly significant abnormal returns of insider sales. There are no significant abnormal returns associated with the insider purchases during the sample period. The robustness of the results regarding all transactions (Model 1) is tested using the five robustness test samples presented in section 5.3.2. The results appear to be robust against different specifications of the normal return model and event clustering. The robustness regressions are presented in Appendix 3.

In the next regressions, the control variables *TS*, *MC*, *PB*, *NoT*, and *Lag* are added to the equation to test, whether the abnormal returns generated by insiders are explained by them. The results of the regressions are presented in Table 12.

Table 12. OLS regression: Abnormal returns and control variables.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Abnormal returns and control variables			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	0.16%	–0.87%	–3.02%
	(0.77)	(0.23)	(**0.00**)
TS (%)	18.72%	94.34%	–8.42%
	(0.30)	(0.17)	(0.79)
MC (B€)	0.12%	0.28%	0.02%
	(**0.00**)	(**0.00**)	(0.66)
PB	–0.02%	–0.45%	–0.02%
	(0.74)	(**0.00**)	(0.80)
NoT	0.08%	0.27%	0.19%
	(0.45)	(**0.05**)	(0.25)
Lag (days)	0.02%	0.04%	0.01%
	(**0.04**)	(**0.00**)	(0.79)
F/Wald test: p-value	(**0.00**)	(**0.00**)	(0.90)
R-squared	0.01	0.05	0.00
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(0.15)	(0.26)	(**0.01**)
Correlation matrix (max)	0.20	0.40	0.08
VIF (max)	1.04	1.20	1.01

Table 12 shows that after controlling for trade size, company size, price-to-book ratio, trading frequency, and notification lag, no significant abnormal returns for all transactions are found. However, the constant term of Model 3 focusing on insider sales remains highly significant and negative suggesting abnormal returns after insider sales. When it comes to the control variables, *MC* coefficients for Models 1 and 2 are significant, and imply that an increase of one billion euros in market capitalization increases the CARs by fractions of a percentage point. This contradicts with the ordinary size anomaly, which suggests that smaller companies earn abnormal returns.

In addition, for Model 1 and 2 the coefficients for *Lag*, and for Model 2 the coefficients for *PB* and *NoT* are significant. Price-to-book ratio is inversely related to profitability suggesting that lower P/B companies have higher CARs after purchases. The value effect reported in the literature suggests the same. Also, higher number of trades per trading day and longer notification lag seem to increase CARs. For *TS* the estimated coefficients are very large, because the trade size is measured as a percentage of market capitalization. Thus, the large coefficients present the hypothetical effect to the CAR if 100% of the company value had been traded.

The residuals of Model 3 are heteroskedastic, and therefore White standard errors are used in t-tests, and Wald test is used instead of F-test for that regression. F test and Wald test results indicate that Models 1 and 2 are significant, but Model 3 is not. It seems that the abnormal returns after sales cannot be explained with the control variables, and thus only constant term is significant. Overall, none of the models are especially good at explaining the variation in CARs with R-squared values below 10%. However, based on maximum VIF values and correlations, multicollinearity is not a problem in the models, and thus the full correlation matrix or detailed VIF values are not presented.

The robustness of the results regarding all transactions is tested using the five robustness test samples presented in section 5.3.2. The results appear to be quite robust against different specifications of the normal return model. For event clustering, the bigger robustness sample (EvClu2) shows similar results to Model 1 excluding the significance of *Lag* coefficient, but the robustness sample with only fully independent events (EvClu1) did not find significant coefficients for any variables. The robustness regressions are presented in Appendix 4.

In the next regressions, the effect of COVID-19 crisis to the insider trading profitability is examined by adding a dummy variable to the equation. The results are presented in Table 13.

Table 13. OLS regression: Abnormal returns and crisis.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis* is a dummy variable for the crisis period. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Abnormal returns and crisis			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	0.55%	–0.17%	–2.88%
	(0.31)	(0.81)	(**0.00**)
Crisis	–0.87%	–1.65%	–0.30
	(0.13)	(**0.03**)	(0.73)
TS (%)	17.60%	94.81%	–8.91%
	(0.52)	(0.41)	(0.77)
MC (B€)	0.13%	0.29%	0.02%
	(**0.00**)	(**0.00**)	(0.64)
PB	–0.03%	–0.46%	–0.02%
	(0.71)	(**0.01**)	(0.78)
NoT	0.09%	0.28%	0.20%
	(0.43)	(**0.04**)	(0.25)
Lag (days)	0.03%	0.04%	0.01%
	(0.12)	(**0.00**)	(0.78)
Wald test: p-value	(**0.00**)	(**0.00**)	(0.95)
R-squared	0.01	0.06	0.00
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.00**)
Correlation matrix (max)	0.20	0.40	0.11
VIF (max)	1.05	1.21	1.04

The results in Table 13 indicate that separating the crisis period from the total sample has only minimal effects to the estimation. The CARs after sales remain negative and highly significant, but no abnormal returns are associated with all transactions or purchases. However, the uncertainty caused by COVID-19 seems to have a significant impact on the short-term profitability of insider purchases. The abnormal returns were around 1.65 percentage points smaller after purchases during the crisis, which could mean that the information asymmetry between insiders and outsiders is smaller during uncertain times.

On the other hand, the results could suggest that insider purchases during crisis were motivated more by signalling purposes than money making, and thus insiders accepted lower returns in exchange for restoring the trust in their company. However, in that case the signalling with purchases was not especially successful, at least in short-term. It should also be noted that the results suggesting lower returns after purchases during the entire crisis might be driven by the expected large negative abnormal returns after purchases during the stock market crash of 2020.

Regarding control variables, the results are similar to the results presented in Table 12. The only difference is that the coefficient for *Lag* is not significant for all transactions anymore. The residuals of all models are heteroskedastic, and therefore White standard errors are used in t-tests, and Wald test is used instead of F-test. Similarly to previous results, Wald test indicates that Models 1 and 2 are significant, but Model 3 is not. R-squared values of the models are small, and multicollinearity of the variables remains at a low level.

The results appear to be quite robust against different specifications of the normal return model. For event clustering, the bigger robustness sample (EvClu2) shows similar results to Model 1, but the robustness sample with only fully independent events (EvClu1) did not find significant coefficients for any variables. The robustness regressions are presented in Appendix 5.

To understand the effects of COVID-19 to the profitability insider trading during the different phases of the crisis, Table 14 presents the OLS regressions where *Crisis* variable is replaced by individual dummy variables for each crisis quarter. As there are only minor changes in the coefficients and significance of the control variables compared to Table 13, they are not presented in Table 14. The full results of the regressions models with the crisis quarters can be viewed in Appendix 6.

Table 14. OLS regression: Abnormal returns and crisis quarters.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, $CAR_{(0,20)P}$ for purchases, and $CAR_{(0,20)S}$ for sales. *Crisis_Q1_20, Crisis_Q2_20, Crisis_Q3_20, Crisis_Q4_20,* and *Crisis_Q1_21* are the dummy variables for the crisis period quarters. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Abnormal returns and crisis quarters			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	0.13%	–1.27%	–3.01%
	(0.81)	(0.07)	(**0.00**)
Crisis_Q1_20	–5.07%	–8.07%	–5.34%
	(**0.00**)	(**0.00**)	(**0.01**)
Crisis_Q2_20	0.75%	–0.09%	–2.35%
	(0.38)	(0.92)	(0.18)
Crisis_Q3_20	1.70%	3.06%	0.28%
	(0.07)	(**0.01**)	(0.86)
Crisis_Q4_20	–0.44%	3.59%	4.85%
	(0.61)	(**0.00**)	(**0.00**)
Crisis_Q1_21	0.90%	–0.13%	–1.73%
	(0.31)	(0.90)	(0.24)
Control variables presented in Appendix 6			
Wald test: p-value	(**0.00)**	(**0.00**)	(**0.00**)
R-squared	0.05	0.15	0.08
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.02**)
Correlation matrix (max)	0.20	0.40	0.24
VIF (max)	1.13	1.26	1.14

Table 14 seems to verify the earlier hypothesis that the changes in the abnormal returns during the first quarter of 2020, when the market crash occurred, explain the lower abnormal returns after purchases during the overall crisis period. The coefficients for Q1 of 2020 are significant for all models. The CARs after purchases during the first quarter were around 8 percentage points smaller than during non-crisis period, whereas the avoided losses after sales transactions were around 5.3 percentage points larger. Earlier it was found that the number of insiders purchases also peaked during the first quarter of 2020, which together with the bigger decline after purchases should explain why the abnormal returns in total (Model 1) were also significantly lower in Q1. In other words, the avoided losses after sales did not cancel out the substantial losses in Q1 after purchases.

On the other hand, there are significantly higher abnormal returns associated with both purchases and sales during the Q4 of 2020 compared to the non-crisis period. Also, the Q3 coefficient is positive and significant for purchases. This indicates that crisis period consisted of different phases and that the changing market conditions also affected the profitability of insider trading. Insiders were not able to make short-term abnormal profits during the crash, but on the other hand even insider sales were followed by positive CARs during Q4. The changes in abnormal returns after purchases and sales during Q4 appear to cancel each other in aggregate, as the coefficient for Model 1 is not significant.

Based on Table 14, the answer for why the profitability of disposals was not affected by the crisis similarly to purchases can be derived. The effect of the crash period was more negative for insider purchases, and in addition the effect of the recovery period in Q4 seems to have been more positive for insider sales. In other words, stocks sold by insiders suffered less in the beginning of the crisis and benefited more in the end of the crisis relative to the non-crisis period. These smaller negative crash effects and larger positive post-crash effects cancel each other better during the total crisis period than in case of purchases. Thus, the earlier reflections based on Figure 9 that the profitability of insider purchases was more affected by the crisis period than sales can be confirmed.

Heteroskedasticity of the residuals is considered in the significance tests of Table 14 and multicollinearity between the independent variables is at an acceptable level. The robustness of the results regarding all transactions is tested using the robustness test samples. As previously, the results appear to be quite robust against different specifications of the normal return model. However, the results are not robust against event clustering. The coefficient of Q1 of 2020 is not significant using either of the robust samples for event clustering. The robustness regressions are presented in Appendix 7.

Finally, the impact of insider position on the profitability of insider trading is investigated. Dummy variables representing transactions by CEOs, CFOs, board members, and other senior managers are included in the regression model. The transactions of closely associated persons are used as the reference group. Table 15 presents the regression results excluding control variables, which show similar coefficients and p-values than in previous regressions. The full results of the regression models with the insider position dummy variables can be viewed in Appendix 8.

Table 15. OLS regression: Insider position.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis* is a dummy variable for the crisis period. *CEO, CFO, MoB,* and *OSM,* are the dummy variables for the insider positions. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Insider position			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	–0.53%	–0.87%	–0.85%
	(0.40)	(0.30)	(0.43)
Crisis	–1.03%	–1.66%	0.13%
	(0.07)	(**0.02**)	(0.89)
CEO	4.11%	2.65%	–5.62%
	(**0.00**)	(**0.03**)	(**0.00**)
CFO	1.74%	–0.61%	–3.42%
	(0.30)	(0.84)	(**0.05**)
MoB	1.30%	1.21%	–2.79%
	(0.05)	(0.11)	(0.07)
OSM	1.22%	0.07%	–2.12%
	(0.11)	(0.95)	(0.09)
Control variables presented in Appendix 8			
Wald test: p-value	(**0.00**)	(**0.00**)	(0.05)
R-squared	0.03	0.06	0.03
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.02**)
Correlation matrix (max)	$\lvert -0.34 \rvert$	0.40	$\lvert -0.35 \rvert$
VIF (max)	1.40	1.29	1.94

Table 15 indicates that the insider transactions by CEOs have earned significantly higher abnormal returns compared to the closely associated persons' trades during the total sample period. The coefficients are significant for all transactions, purchases, and sales. The results support the information hierarchy hypothesis, which suggests that higher managers, such as CEOs, possess greater knowledge of the business, and therefore generate higher abnormal returns. For insider sales, also CFOs' trades seem to earn higher abnormal returns.

The results of Table 15 are quite robust against different specifications of the normal return model and event clustering, although the robustness sample with only fully independent events did not find significantly higher returns for CEOs but CFOs. Other robustness samples verified the CEO anomaly, but some of them also reported significantly higher abnormal returns for other insiders. The robustness regressions are presented in Appendix 9. Moreover, heteroskedasticity of the residuals is considered in the significance tests and multicollinearity is at a low level.

The regression equation used in Table 15 assumes that the differences in profitability between the four insider types and the reference group were not affected by the COVID-19 crisis. To examine whether this assumption is true, interaction dummy variables *CEO_Crisis, CFO_Crisis*, *MoB_Crisis*, and *OSM_crisis* are added to the equation. The results are presented in Table 16. The full results of the regression models including also control variables can be viewed in Appendix 10.

Table 16. OLS regression: Insider position and crisis.

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis* is a dummy variable for the crisis period. *CEO, CFO, MoB,* and *OSM,* are the dummy variables for the insider positions. *CEO_Crisis, CFO_Crisis, MoB_Crisis,* and *OSM_crisis,* are the interaction dummy variables for the insider positions and crisis. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Insider position and crisis			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	–0.14%	–0.40%	–1.10%
	(0.84)	(0.66)	(0.33)
Crisis	–1.86%	–2.55%	0.63%
	(0.05)	(**0.02**)	(0.76)
CEO	2.63%	0.27%	–6.03%
	(0.07)	(0.86)	(**0.02**)
CFO	3.94%	3.09%	–4.32%
	(**0.00**)	(0.13)	(**0.01**)
MoB	0.74%	0.26%	–4.65%
	(0.35)	(0.77)	(**0.02**)
OSM	0.37%	–0.46%	–1.03%
	(0.66)	(0.73)	(0.40)
CEO_Crisis	2.78%	4.60%	0.49%
	(0.14)	(0.05)	(0.88)
CFO_Crisis	–3.81%	–6.44%	1.54%
	(0.22)	(0.22)	(0.65)
MoB_Crisis	1.24%	2.10%	3.21%
	(0.36)	(0.16)	(0.30)
OSM_Crisis	1.89%	1.22%	–2.34%
	(0.22)	(0.62)	(0.35)
Control variables presented in Appendix 10			
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.01**)
R-squared	0.03	0.08	0.05
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.01**)
Correlation matrix (max)	0.74	0.75	0.76
VIF (max)	3.10	2.72	5.08

The results in Table 16 indicate that there are differences in the profitability of the trades of different insider types between non-crisis and crisis period. Firstly, during non-crisis period, insider sales by CEOs, CFOs and Board members are followed by significantly lower negative abnormal returns than the trades of closely associated persons. This indicates that high ranking insiders are able to avoid higher losses during the non-crisis period. However, after purchases there are no similar findings. In total, CFOs earn significantly higher abnormal returns during the non-crisis period.

When it comes to the crisis period, there are no significant changes in the insider trading profitability during it. However, CEO purchases are followed by higher abnormal returns at the 10% significance level and the p-value is very close to 5% threshold. It seems that CEOs increased their abnormal returns during the crisis, which is noteworthy considering that based on Table 10, the number of CEO trades was also significantly higher during the crisis. Earlier it was hypothesized that CEOs traded more during the crisis due to superior information or signalling motives. As the abnormal returns after purchases were higher for CEOs than other insiders during the crisis based on Table 16, it seems that the money-making motive is more plausible of the two explanations. At the same time, it should be remembered that closed periods affected the timing of trades, and CEOs might have been more fortunate with their timing than other insiders in different companies during the crisis.

The reason why there were no significantly higher returns for CFOs during the total sample period, as reported in Table 15, seems to be that although CFOs traded more profitably during the non-crisis period, their trades were performing substantially worse than trades made by closely associated persons during COVID-19. This is completely opposite to how the profitability of CEO trades was affected by the crisis. In hindsight, it seems that outside investor would have gotten the best returns by following CFO trades during the non-crisis period and CEO trades during the crisis period.

The results of Table 16 are quite robust against different specifications of the normal return model and event clustering, although the robustness sample with only fully independent events did not find significantly higher returns for CFOs during non-crisis period. The robustness regressions are presented in Appendix 11. Moreover, heteroskedasticity of the residuals is considered in the significance tests. The correlations between insider type dummy variables and interaction dummy variables are close to the 0.80 threshold, but based on the VIF values, multicollinearity should not be a problem in the regressions.

6.3.3 Discussion

The key findings of the OLS regressions can be summarized as follows. Insiders earn significant abnormal returns only after sales when the control variables are considered. In other words, they are generally able to avoid abnormal losses with their trades during the total sample period. During the crisis period from 1/1/2020 to 31/3/2021 the only significant effect to the trading profitability is that the abnormal returns after purchases are lower. This result is caused by the large negative effect of the stock market crash of 2020. Later during the crisis, the abnormal returns are significantly more positive after purchases and sales than during the non-crisis period. Lastly, CEO trades are associated with significantly higher CARs during the total sample period, but when the effect of the crisis is considered, only the abnormal returns of the CFO trades during the non-crisis period are significantly different from the returns of the closely associated persons' trades.

Firstly, the results support the common hypothesis that insiders generate abnormal returns with their trades. This has also been the conclusion of the most previous insider trading studies presented in Table 1 in section 2.3.1. Consequently, the results imply that the markets are not efficient in the strong form. However, the results suggest that only insider sales are followed with significant abnormal returns. This is against the rationale that insiders have many reasons to sell but are buying only to make money. Thus, the results on the information value of purchases and sales contradict with some previous studies such as Lakonishok and Lee (2001) and are supportive to others such as Del Brio et al. (2002).

Secondly, the uncertainty caused by COVID-19 did not affect the overall profitability of insider trading. However, it had a negative impact on the profitability of insider purchases. This result is different from the results of Van Geyt et al. (2013), who found that the uncertainty produced by the financial crisis increased the profitability of insider trading. When dividing the crisis period on a quarterly basis, it can be stated that the effect on the profitability changed throughout the crisis. In the beginning of the crisis the abnormal returns were more negative and later more positive. Especially, the effect of the stock market crash of 2020 seems to be driving the coefficients. Thus, the definition of the crisis period has a big impact on the results. However, it should be noted that the results concerning crisis quarters are not robust against event clustering.

Thirdly, the results on the higher signal value of CEO and CFO trades are consistent with the previous research by Seyhun (1986) and Lin and Howe (1990), who found supportive evidence on the information hierarchy hypothesis. It also seems that macroeconomic crises might influence the profitability differences between the insider groups, although the results of this thesis were only significant at 10% level.

It should be emphasized that the time frame of the profitability analysis is very short, only 21 trading days. The fact that insider purchases were followed by high negative returns during the stock market crash does not necessarily mean that the trades were unsuccessful. As reported earlier in the thesis, insider trading behaviour during the crash was indicative of the returns during a six-month post-crash period. It is unlikely that the trading horizon of insiders would have been only 21 days and thus this approach does not estimate the extent of the realized returns for insiders. Due to the short event window, also the results contradicting with the size effect and suggesting higher abnormal returns for big firms should be approached with caution.

Moreover, the motivation for insiders to trade during the crash of 2020 might have been signalling instead of money making. If increased insider purchasing during the crash helped restore outside investors' trust in their firms, the short-term negative abnormal returns might have been a conscious sacrifice by top management to secure their jobs. On the other hand, the effectiveness of their signalling is debatable. Overall, the results imply that insider trades are not free from the effects of the general market turbulence. If the stock market is going down, it appears to do so independent of insiders’ behaviour and also affects their trading profitability. Even though insiders were signalling the existence of lucrative purchase opportunities with increased purchasing during the crash, the short-term returns of the trades were highly negative. On the other hand, when prices were rising in the end of 2020, even insider sales were followed by positive abnormal returns.

Lastly, the results of the event study do not provide evidence for the hypothesis that uncertainty in the markets would benefit inside investors in the short-term. Insiders’ sales are followed by similar abnormal returns independent from the uncertainty level. Insider purchases do not generate abnormal returns even during the non-crisis period, and the returns are significantly lower during the crisis. Therefore, it seems that whatever happens to the information asymmetry between insiders and outsiders during the crisis, it is not in the interest of insiders that the market uncertainty level increases.

7 Conclusion

The objective of the thesis was to understand the effects of COVID-19 pandemic to insider trading in the Finnish stock market using aggregate insider trading approach and event study methodology. The specific focus areas were the stock market crash of 2020 and the effect of COVID-19 related uncertainty on the short-term profitability of insider trading. Previous research suggested that insider trading during stock market crashes can be indicative of the post-crash returns of the companies. Moreover, macroeconomic crises have previously found to have an impact on the short-term profitability of insider trading.

To answer the first research question of thesis, the corporate insider response to the stock market crash of 2020 was examined using various insider trading measures. The estimated time series regression models suggest that the number of insider purchases was significantly lower preceding the crash and significantly higher during the crash. This indicates that insiders were cautious in their purchases before the crash but viewed the crash period as a good opportunity to buy. It seems that insiders did not perceive the effects of COVID-19 as detrimental to their businesses than other investors. Alternatively, they used purchasing as way to signal confidence in their firm. The timing of the trades during the crisis was affected by the closed periods of insiders. Apart from the number of insider purchases, no other insider trading measure including volume-based and monetary-based variables showed significant changes around the market crash.

The second research question focused on the post-crash performance of the stocks that insiders traded during the market crash. The performance of stocks during 6, 12, and 18 months after the crash was explained by changes in insider trading ratios, while controlling for company risk level, company size, price-to-book ratio, and the contrarian strategy. The analysis was conducted using grouped observations and WLS regression models. The results show that the stocks purchased more by insiders during the crash generated higher returns during the following 6 months. This effect was significant for monetary-based trading ratio at 5% significance level and for other ratios at 10% significance level.

The results suggest that insiders seem to have been able to identify undervalued stocks during the crash of 2020. It also supports the hypothesis that the primary motive for increased purchasing during the crash was money-making and not signalling. However, when using the 12-month and 18-month post-crash return periods, no significant connections between the changes in insider trading ratios during the crash and the post-crash returns were found. This indicates that insiders either identify only short-term undervaluations in stocks during crashes or that the 6-month returns are an outlier, possibly caused by signalling, among the post-crash return time frames. Moreover, it must be emphasized that the reliability of the WLS regression results is questionable due to small sample size, grouping of the stocks, and multicollinearity in the models.

In the third research question the effect of COVID-19 pandemic to the short-term profitability of insider trading was considered using the event study methodology and OLS regression models. The results suggest that in the sample from 2019 to 2021 only insider sales were followed by significant abnormal returns. The COVID-19 crisis did not influence the profitability of sales, but abnormal returns after purchases were significantly lower during the crisis. The underlying reason for these results is that the highly significant and negative short-term abnormal returns from the stock market crash of 2020 had a greater impact on the total profitability of purchases during the crisis period compared to sales. Whether insiders purchased shares during the crash due to poor short-term judgment, in anticipation of significant long-term returns, or for signaling purposes remains debatable.

In addition, CEO trades earned significantly higher abnormal returns than the trades of other insiders during the total sample period. When the variability in the profitability differences between insiders during the crisis and non-crisis period is considered, CFO trades are significantly more profitable during the non-crisis period than others. Although CEO returns after purchases are significantly higher during the crisis period only at 10% significance level, it indicates the profitability differences between insiders might be affected by macroeconomic crises. Also, it seems that at least CEO trades during the crisis were motivated by superior information rather than signalling. Most results of the event study part are robust to different specifications of the normal return model and to some extent also against the issue of event clustering.

All in all, the results of the thesis show that macroeconomic crises, such as COVID-19, have significant implications for insider trading. Crises and crashes appear to affect the timing of insider trades, and the trades then convey the views of the most informed market participants to the outside investors. Although the existence of false signals among insider trades cannot be ruled out, most insider trading seems to be motivated by financial gain. Moreover, the profitability of insider trading is not immune to the impact of market turbulence, and in the case of COVID-19 this effect was not positive.

There are still many open questions left for the future research. For instance, as Figure 2 in section 4.1.2 suggests, the pace of the recovery after the crash of 2020 varied substantially between industries. Thus, an industry level analysis of COVID-19 effects and insider trading is needed. This thesis focused on the companies in the main list of Nasdaq Helsinki, but a similar analysis could be conducted using a sample of growth companies from Nasdaq First North Growth Market. In addition, long-term profitability of the insider trades using the event study methodology and longer event windows would be a valuable extension to the results of this thesis.

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Appendices

Appendix 1: WLS – Correlation matrix and VIF values

Correlation matrix: WLS regressions independent variables							
	ΔPRAT	**ΔSPRAT**	**ΔEPRAT**	**R_c**	**β**	**MC**	**PB**
ΔPRAT	1.00						
ΔSPRAT		1.00					
ΔEPRAT			1.00				
R_c	–0.13	–0.01	0.06	1.00			
β	0.17	0.12	0.00	–0.57	1.00		
MC	0.17	0.26	0.08	–0.21	<u>0.86</u>	1.00	
PB	0.38	0.35	0.14	0.15	-0.22	0.00	1.00

VIF values: WLS regressions independent variables					
Model 1	**ΔPRAT**	**R_c**	**β**	**MC**	**PB**
	1.15	2.46	<u>11.84</u>	8.80	1.69
Model 2	**ΔSPRAT**	**R_c**	**β**	**MC**	**PB**
	1.17	2.42	<u>11.24</u>	8.92	1.59
Model 3	**ΔEPRAT**	**R_c**	**β**	**MC**	**PB**
	1.11	2.42	<u>11.25</u>	8.83	1.68

Appendix 2: WLS regression – 18-month returns

The dependent variable is the 18-month post-crash return. The independent variables are the change in insider trading ratios *PRAT*, *SPRAT*, and *EPRAT*, crash returns R_c, risk measure β, natural logarithm of market capitalization *MC*, and price-to-book ratio *PB*. Model diagnostics include the Jarque-Bera test for normality, the special case of White test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded. Sample size is 9 in all regressions.

Weighted least squares regression: 18-month post-crash returns			
	Model 1 (ΔPRAT)	**Model 2 (ΔSPRAT)**	**Model 3 (ΔEPRAT)**
Constant	4.48	4.77	4.52
	(0.26)	(0.21)	(0.26)
ΔInsider trading variable	0.01	0.08	0.00
	(0.95)	(0.52)	(0.99)
R_c	-4.41	-4.54	–4.38
	(0.38)	(0.33)	(0.38)
β	0.73	0.79	0.75
	(0.59)	(0.52)	(0.57)
MC	–0.28	–0.30	–0.28
	(0.16)	(0.12)	(0.16)
PB	0.23	0.23	0.23
	(**0.03**)	(**0.02**)	(**0.03**)
Multiple R-squared	0.89	0.91	0.89
Adjusted R-squared	0.71	0.76	0.71
F-test: p-value	(0.11)	(0.09)	(0.11)
Model diagnostics			
Jarque-Bera: p-value	(0.69)	(0.76)	(0.70)
White test: p-value	(0.36)	(0.72)	(0.32)
Correlation matrix (max)	0.86	0.86	0.86
VIF (max)	11.84	11.24	11.25

Appendix 3: OLS robustness – Abnormal returns 2019–2021

$CAR_{(0,20)}$ is cumulative abnormal return for all events. NoDim refers to $CAR_{(0,20)}$ series calculated with no Dimson adjustment, OMXH25 to $CAR_{(0,20)}$ series, which is calculated with OMXH25 total return series as the proxy for market portfolio, and RepDay refers to $CAR_{(0,20)}$ series, where notification date is used as the event day. EvClu1 is $CAR_{(0,20)}$ series with only fully independent events, and EvClu2 considers also the last events of the event clusters. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Abnormal returns 2019–2021					
$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant (%)	1.04%	1.01%	1.04%	1.68%	1.11%
	(**0.00**)	(**0.00**)	(**0.00**)	(**0.02**)	(**0.01**)
Sample size	1229	1229	1229	206	509

Appendix 4: OLS robustness – Abnormal returns and control variables

$CAR_{(0,20)}$ is cumulative abnormal return for all events. NoDim refers to $CAR_{(0,20)}$ series calculated with no Dimson adjustment, OMXH25 to $CAR_{(0,20)}$ series, which is calculated with OMXH25 total return series as the proxy for market portfolio, and RepDay refers to $CAR_{(0,20)}$ series, where notification date is used as the event day. EvClu1 is $CAR_{(0,20)}$ series with only fully independent events, and EvClu2 considers also the last events of the event clusters. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Abnormal returns and control variables					
$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant	0.18%	0.17%	–0.06%	1.50%	1.06%
	(0.75)	(0.76)	(0.92)	(0.26)	(0.19)
TS (%)	18.40%	17.87%	28.41%	19.56%	16.61%
	(0.31)	(0.34)	(0.16)	(0.36)	(0.35)
MC (B€)	0.11%	0.10%	0.12%	0.00%	0.13%
	(**0.00**)	(**0.01**)	(**0.00**)	(0.97)	(**0.04**)
PB	0.02%	0.03%	–0.02%	0.08%	0.03%
	(0.71)	(0.68)	(0.71)	(0.45)	(0.67)
NoT	0.08%	0.07%	0.17%	–0.05%	–0.14%
	(0.50)	(0.52)	(0.11)	(0.88)	(0.43)
Lag (days)	0.02%	0.02%	0.02%	–0.03%	0.00%
	(**0.04**)	(**0.04**)	(**0.04**)	(0.48)	(0.95)
F test: p-value	(**0.01**)	(**0.02**)	(**0.00**)	(0.87)	(0.32)
R-squared	0.01	0.01	0.02	0.01	0.01
Sample size	1229	1229	1229	206	509
Model diagnostics					
Koenker test: p-value	(0.15)	(0.14)	(0.07)	(0.78)	(0.21)
Correlation matrix (max)	0.20	0.20	0.20	0.09	0.08
VIF (max)	1.04	1.04	1.04	1.01	1.01

Appendix 5: OLS robustness – Abnormal returns and crisis

$CAR_{(0,20)}$ is cumulative abnormal return for all events. NoDim refers to $CAR_{(0,20)}$ series calculated with no Dimson adjustment, OMXH25 to $CAR_{(0,20)}$ series, which is calculated with OMXH25 total return series as the proxy for market portfolio, and RepDay refers to $CAR_{(0,20)}$ series, where notification date is used as the event day. EvClu1 is $CAR_{(0,20)}$ series with only fully independent events, and EvClu2 considers also the last events of the event clusters. *Crisis* is a dummy variable for the crisis period. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Abnormal returns and crisis					
$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant	0.52%	0.52%	0.21%	1.26%	0.67%
	(0.34)	(0.34)	(0.69)	(0.38)	(0.45)
Crisis	–0.79%	–0.80%	–0.61%	0.69%	0.95%
	(0.18)	(0.18)	(0.27)	(0.66)	(0.27)
TS (%)	17.38%	16.84%	27.71%	20.31%	17.87%
	(0.53)	(0.54)	(**0.02**)	(0.34)	(0.32)
MC (B€)	0.12%	0.11%	0.13%	0.00%	0.12%
	(**0.00**)	(**0.00**)	(**0.00**)	(0.97)	(**0.04**)
PB	0.02%	0.02%	–0.03%	0.08%	0.04%
	(0.78)	(0.75)	(0.77)	(0.44)	(0.65)
NoT	0.08%	0.08%	0.17%	–0.06%	–0.15%
	(0.47)	(0.50)	(0.12)	(0.86)	(0.39)
Lag (days)	0.03%	0.03%	0.02%	–0.03%	–0.00
	(0.13)	(0.13)	(0.05)	(0.45)	(0.99)
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.91)	(0.32)
R-squared	0.01	0.01	0.02	0.01	0.01
Sample size	1229	1229	1229	206	509
Model diagnostics					
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.50)	(0.12)
Correlation matrix (max)	0.20	0.20	0.20	0.11	0.08
VIF (max)	1.05	1.05	1.05	1.02	1.02

Appendix 6: OLS regression – Abnormal returns and crisis quarters

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis_Q1_20, Crisis_Q2_20, Crisis_Q3_20, Crisis_Q4_20,* and *Crisis_Q1_21* are the dummy variables for the crisis period quarters. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Abnormal returns and crisis quarters			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	0.13%	–1.27%	–3.01%
	(0.81)	(0.07)	(**0.00**)
Crisis_Q1_20	–5.07%	–8.07%	–5.34%
	(**0.00**)	(**0.00**)	(**0.01**)
Crisis_Q2_20	0.75%	–0.09%	–2.35%
	(0.38)	(0.92)	(0.18)
Crisis_Q3_20	1.70%	3.06%	0.28%
	(0.07)	(**0.01**)	(0.86)
Crisis_Q4_20	–0.44%	3.59%	4.85%
	(0.61)	(**0.00**)	(**0.00**)
Crisis_Q1_21	0.90%	–0.13%	–1.73%
	(0.31)	(0.90)	(0.24)
TS (%)	15.64%	57.47%	–10.25%
	(0.57)	(0.51)	(0.74)
MC (B€)	0.13%	0.30%	–0.00%
	(**0.00**)	(**0.00**)	(0.92)
PB	–0.03%	–0.42%	0.01%
	(0.64)	(**0.02**)	(0.91)
NoT	0.21%	0.53%	0.20%
	(0.07)	(**0.00**)	(0.27)
Lag (days)	0.03%	0.05%	0.03%
	(0.08)	(**0.00**)	(0.51)
Wald test: p-value	(**0.00**)	(**0.00**)	(**0.00**)
R-squared	0.05	0.15	0.08
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.02**)
Correlation matrix (max)	0.20	0.40	0.24
VIF (max)	1.13	1.26	1.14

Appendix 7: OLS robustness – Abnormal returns and crisis quarters

$CAR_{(0,20)}$ is return for all events. NoDim refers to $CAR_{(0,20)}$ series calculated with no Dimson adjustment, OMXH25 to $CAR_{(0,20)}$ series, which is calculated with OMXH25 total return series, and RepDay refers to $CAR_{(0,20)}$ series, where notification date is the event day. EvClu1 is $CAR_{(0,20)}$ series with only fully independent events, and EvClu2 considers also the last events of the event clusters. *Crisis_Q1_20, Crisis_Q2_20, Crisis_Q3_20, Crisis_Q4_20,* and *Crisis_Q1_21* are the dummy variables for the crisis period quarters. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Koenker test is for heteroskedasticity, and maximum cross-correlation and VIF values are reported. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Abnormal returns and crisis quarters

$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant	0.14%	0.13%	–0.18%	1.18%	0.54%
	(0.80)	(0.82)	(0.74)	(0.42)	(0.54)
Crisis_Q1_20	–4.58%	–4.80%	–4.20%	–1.14%	–0.84%
	(**0.00**)	(**0.00**)	(**0.00**)	(0.69)	(0.57)
Crisis_Q2_20	0.65%	0.80%	1.13%	1.39%	1.17%
	(0.44)	(0.34)	(0.16)	(0.64)	(0.45)
Crisis_Q3_20	1.65%	1.71%	2.41%	–0.61%	1.33%
	(0.07)	(0.06)	(**0.01**)	(0.84)	(0.42)
Crisis_Q4_20	–0.42%	–0.38%	–0.28%	0.73%	1.05%
	(0.63)	(0.67)	(0.75)	(0.82)	(0.48)
Crisis_Q1_21	0.79%	0.80%	–0.07%	3.00%	2.16%
	(0.38)	(0.38)	(0.92)	(0.29)	(0.14)
TS (%)	15.61%	14.99%	25.70%	19.94%	17.35
	(0.57)	(0.59)	(**0.03**)	(0.36)	(0.33)
MC (B€)	0.12%	0.11%	0.13%	–0.01%	0.12
	(0.00)	(**0.00**)	(**0.00**)	(0.96)	(0.05)
PB	0.01%	0.02%	–0.03%	0.09%	0.04
	(0.85)	(0.82)	(0.74)	(0.42)	(0.65)
NoT	0.19%	0.19%	0.27%	–0.03%	–0.12
	(0.10)	(0.10)	(**0.01**)	(0.93)	(0.53)
Lag (days)	0.03%	0.03%	0.03%	–0.03%	0.00
	(0.09)	(0.09)	(**0.02**)	(0.52)	(0.85)
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.96)	(0.47)
R-squared	0.04	0.04	0.05	0.02	0.02
Sample size	1229	1229	1229	206	509
Model diagnostics					
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.54)	(0.06)
Correlation matrix (max)	0.20	0.20	0.20	0.18	0.16
VIF (max)	1.13	1.13	1.13	1.10	1.12

Appendix 8: OLS regression – Insider position

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis* is a dummy variable for the crisis period. *CEO, CFO, MoB,* and *OSM,* are the dummy variables for the insider positions. *TS* refers to trade size, *MC* refers to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Model diagnostics include Koenker test for heteroskedasticity, and maximum cross-correlation and VIF values. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Insider position			
	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	–0.53%	–0.87%	–0.85%
	(0.40)	(0.30)	(0.43)
Crisis	–1.03%	–1.66%	0.13%
	(0.07)	(**0.02**)	(0.89)
CEO	4.11%	2.65%	–5.62%
	(**0.00**)	(**0.03**)	(**0.00**)
CFO	1.74%	–0.61%	–3.42%
	(0.30)	(0.84)	(**0.05**)
MoB	1.30%	1.21%	–2.79%
	(0.05)	(0.11)	(0.07)
OSM	1.22%	0.07%	–2.12%
	(0.11)	(0.95)	(0.09)
TS (%)	15.20%	103.42%	–3.96%
	(0.55)	(0.38)	(0.89)
MC (B€)	0.14%	0.30%	0.02%
	(**0.00**)	(**0.00**)	(0.70)
PB	–0.03%	–0.45%	–0.01
	(0.63)	(**0.01**)	(0.92)
NoT	0.09%	0.30%	0.21
	(0.46)	(**0.04**)	(0.21)
Lag (days)	0.03%	0.04%	0.01
	(0.10)	(**0.00**)	(0.90)
Wald test: p-value	(**0.00**)	(**0.00**)	(0.05)
R-squared	0.03	0.06	0.03
Sample size	1229	787	442
Model diagnostics			
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.02**)
Correlation matrix (max)	$\lvert -0.34 \rvert$	0.40	$\lvert -0.35 \rvert$
VIF (max)	1.40	1.29	1.94

Appendix 9: OLS robustness – Insider position

CAR(0,20) is return for all events. NoDim refers to CAR(0,20) calculated with no Dimson adjustment, OMXH25 to CAR(0,20) calculated with OMXH25 total return series, and RepDay to CAR(0,20), where notification date is the event day. EvClu1 is CAR(0,20) series with only fully independent events, and EvClu2 considers also the last events of the event clusters. *Crisis* refers to the crisis period. *CEO, CFO, MoB,* and *OSM,* refer to the insider positions. *TS* refers to trade size, *MC* to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Koenker test is for heteroskedasticity, and maximum cross-correlation and VIF values are reported. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Insider position					
CAR(0,20)	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant	–0.50%	–0.60%	–0.87%	–1.84%	–1.36%
	(0.44)	(0.36)	(0.16)	(0.40)	(0.22)
Crisis	–0.94%	–0.95%	–0.68%	0.42%	0.79%
	(0.10)	(0.11)	(0.21)	(0.79)	(0.35)
CEO	3.88%	4.06%	2.71%	5.01%	4.50%
	(**0.00**)	(**0.00**)	(**0.00**)	(0.08)	(**0.00**)
CFO	1.57%	1.47%	0.53%	8.36%	7.05%
	(0.35)	(0.39)	(0.72)	(**0.02**)	(**0.00**)
MoB	1.26%	1.43%	1.58%	3.93%	2.39%
	(0.06)	(**0.04**)	(**0.02**)	(0.09)	(**0.04**)
OSM	1.13%	1.30%	1.65%	2.27%	2.24%
	(0.14)	(0.10)	(**0.02**)	(0.36)	(0.05)
TS (%)	15.05%	14.46%	27.15%	18.37%	17.50%
	(0.55)	(0.57)	(**0.01**)	(0.39)	(0.32)
MC (B€)	0.13%	0.12%	0.14%	0.02%	0.13%
	(**0.00**)	(**0.00**)	(**0.00**)	(0.87)	(**0.03**)
PB	0.01%	0.01%	–0.04%	0.11%	0.02%
	(0.86)	(0.86)	(0.62)	(0.32)	(0.77)
NoT	0.08%	0.08%	0.18%	–0.14%	–0.19%
	(0.50)	(0.51)	(0.11)	(0.66)	(0.29)
Lag (days)	0.03%	0.03%	0.03%	–0.01%	0.00%
	(0.11)	(0.11)	(**0.05**)	(0.79)	(0.85)
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.53)	(**0.01**)
R-squared	0.02	0.02	0.03	0.04	0.05
Sample size	1229	1229	1229	206	509
Model diagnostics					
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.57)	(0.07)
Correlation matrix (max)	$\lvert -0.34\rvert$	$\lvert -0.34\rvert$	$\lvert -0.34\rvert$	$\lvert -0.47\rvert$	$\lvert -0.40\rvert$
VIF (max)	1.40	1.40	1.40	2.27	1.61

Appendix 10: OLS regression – Insider position and crisis

$CAR_{(0,20)}$ is cumulative abnormal return for all events, *$CAR_{(0,20)P}$* for purchases, and *$CAR_{(0,20)S}$* for sales. *Crisis* refers to the crisis period. *CEO, CFO, MoB,* and *OSM,* are the dummy variables for the insider positions. *CEO_Crisis, CFO_Crisis, MoB_Crisis,* and *OSM_crisis,* are the interaction dummy variables for the insider positions and crisis. *TS* refers to trade size, *MC* to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Koenker test is for heteroskedasticity, and maximum cross-correlation and VIF values are reported. P-values of the significance tests are presented in brackets. Significant p-values at the 5% level are bolded.

OLS regression: Insider position and crisis

	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
Constant	–0.14%	–0.40%	–1.10%
	(0.84)	(0.66)	(0.33)
Crisis	–1.86%	–2.55%	0.63%
	(0.05)	(**0.02**)	(0.76)
CEO	2.63%	0.27%	–6.03%
	(0.07)	(0.86)	(**0.02**)
CFO	3.94%	3.09%	–4.32%
	(**0.00**)	(0.13)	(**0.01**)
MoB	0.74%	0.26%	–4.65%
	(0.35)	(0.77)	(**0.02**)
OSM	0.37%	–0.46%	–1.03%
	(0.66)	(0.73)	(0.40)
CEO_Crisis	2.78%	4.60%	0.49%
	(0.14)	(0.05)	(0.88)
CFO_Crisis	–3.81%	–6.44%	1.54%
	(0.22)	(0.22)	(0.65)
MoB_Crisis	1.24%	2.10%	3.21%
	(0.36)	(0.16)	(0.30)
OSM_Crisis	1.89%	1.22%	–2.34%
	(0.22)	(0.62)	(0.35)
TS (%)	17.14%	103.82%	–0.12%
	(0.51)	(0.39)	(1.00)
MC (B€)	0.15%	0.30%	0.02%
	(**0.00**)	(**0.00**)	(0.68)
PB	–0.04%	–0.46%	–0.01%
	(0.59)	(**0.01**)	(0.91)
NoT	0.08%	0.28%	0.22%
	(0.50)	(**0.04)**	(0.18)
Lag (days)	0.03%	0.05%	0.01%
	(0.08)	(**0.00**)	(0.91)

	Model 1 ($CAR_{(0,20)}$)	**Model 2 ($CAR_{(0,20)P}$)**	**Model 3 ($CAR_{(0,20)S}$)**
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.01**)
R-squared	0.03	0.08	0.05
Sample size	1229	787	442
	Model diagnostics		
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.01**)
Correlation matrix (max)	0.74	0.75	0.76
VIF (max)	3.10	2.72	5.08

Appendix 11: OLS robustness – Insider position and crisis

CAR(0,20) is return for all events. NoDim refers to $CAR_{(0,20)}$ calculated with no Dimson adjustment, OMXH25 to $CAR_{(0,20)}$ calculated with OMXH25 total return series, and RepDay to $CAR_{(0,20)}$, where notification date is the event day. EvClu1 is $CAR_{(0,20)}$ series with fully independent events, and EvClu2 considers also the last events of the event clusters. *Crisis* refers to the crisis period. *CEO, CFO, MoB,* and *OSM,* refer to the insider positions. *CEO_Crisis, CFO_Crisis, MoB_Crisis,* and *OSM_crisis,* are the interaction dummy variables. *TS* refers to trade size, *MC* to market capitalization in billion euros, *PB* is the price-to-book ratio, *NoT* is the number of trades per trading day, and *Lag* is the number of days between the transaction and the notification. Koenker test is for heteroskedasticity, and maximum cross-correlation and VIF values are reported. P-values of the significance tests are in brackets. Significant p-values at the 5% level are bolded.

OLS robustness: Insider position and crisis

$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Constant	–0.07%	–0.12%	–0.82%	–0.36%	–0.97%
	(0.92)	(0.86)	(0.22)	(0.89)	(0.45)
Crisis	–1.82%	–1.95%	–0.75%	–3.39%	–0.12%
	(0.05)	(**0.04**)	(0.39)	(0.39)	(0.94)
CEO	2.61%	2.70%	2.76%	3.97%	3.80%
	(0.07)	(0.06)	(**0.05**)	(0.29)	(0.09)
CFO	3.73%	3.76%	4.52%	7.94%	7.52%
	(**0.00**)	(**0.00**)	(**0.00**)	(0.11)	(**0.01**)
MoB	0.71%	0.81%	1.16%	2.38%	2.51%
	(0.38)	(0.31)	(0.15)	(0.43)	(0.11)
OSM	0.10%	0.15%	1.11%	–0.44%	0.99%
	(0.91)	(0.86)	(0.17)	(0.89)	(0.52)
CEO_Crisis	2.42%	2.60%	–0.05%	2.59%	1.43%
	(0.20)	(0.18)	(0.98)	(0.64)	(0.64)
CFO_Crisis	–3.71%	–3.94%	–7.19%	1.46%	–0.83%
	(0.24)	(0.22)	(**0.01**)	(0.84)	(0.83)
MoB_Crisis	1.20%	1.36%	0.94%	3.61%	–0.27%
	(0.37)	(0.32)	(0.47)	(0.45)	(0.91)
OSM_Crisis	2.26%	2.53%	1.21%	7.40%	2.89%
	(0.14)	(011)	(0.40)	(0.14)	(0.20)
TS (%)	16.59%	16.09%	27.72%	17.17%	17.04%
	(0.52)	(0.53)	(**0.01**)	(0.43)	(0.34)
MC (B€)	0.13%	0.13%	0.15%	0.02%	0.13%
	(0.00)	(**0.00**)	(**0.00**)	(0.87)	(**0.04**)
PB	0.01%	0.01%	–0.05%	0.11%	0.02%
	(0.91)	(0.91)	(0.58)	(0.33)	(0.80)
NoT	0.07%	0.07%	0.16%	–0.11%	–0.17%
	(0.54)	(0.56)	(0.13)	(0.75)	(0.33)

$CAR_{(0,20)}$	**NoDim**	**OMXH25**	**RepDay**	**EvClu1**	**EvClu2**
Lag (days)	0.03%	0.03%	0.03%	–0.00%	0.00%
	(0.08)	(0.08)	(0.02)	(0.91)	(0.80)
F/Wald test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.63)	(**0.02**)
R-squared	0.03	0.03	0.04	0.06	0.05
Sample size	1229	1229	1229	206	509
Model diagnostics					
Koenker test: p-value	(**0.00**)	(**0.00**)	(**0.00**)	(0.60)	(0.08)
Correlation matrix (max)	0.74	0.74	0.74	0.67	0.72
VIF (max)	3.10	3.10	3.10	6.50	3.86