# THE INSIDER SCOOP

## A STUDY ON THE EFFECT OF INSIDER TRADING AND ABNORMAL STOCK RETURNS DURING UNCERTAIN MARKET CONDITIONS OF THE RUSSIAN-UKRAINE WAR

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# The Insider Scoop: A Study on the Effect of Insider Trading and Abnormal Stock Returns During Uncertain Market Condition of the Russia-Ukraine War

Abstract: This paper examines how insider transactions of stocks listed on Nasdaq Stockholm generate abnormal returns during the period 2016-2022 and extends on how abnormal returns react in times of uncertainty, i.e., after the Invasion of Ukraine. Our findings suggest that there are smaller abnormal returns connected with insider trading in the timeframe of 2016-2022, but not necessarily as highly connected in times of uncertainty. This paper confirms the foundation set by previous studies, even though the stock market has gone through a shift of paradigm. Ultimately this thesis opens for more in-depth future research revolving around the new environment of the capital market along with insider trading and the behavioral phenomenon around it.

Keywords:

Russian-Ukrainian War, Insider Trading, Abnormal Stock Return, Nasdaq Stockholm, Uncertainty

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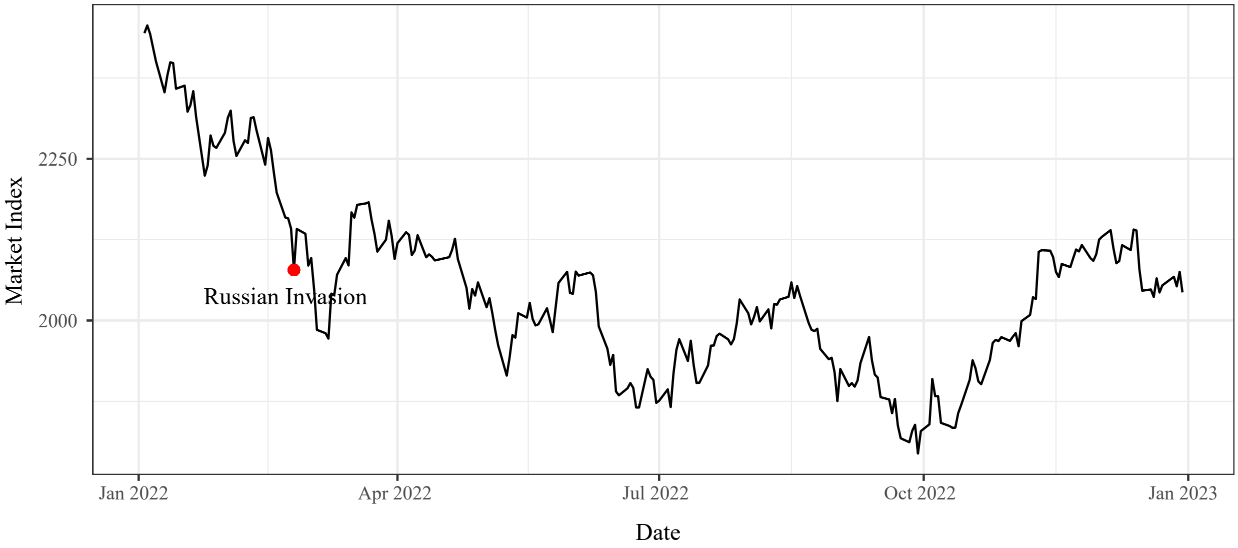
# Introduction

On the 24th of February, 2022, the entire world, and particularly Ukraine, experienced a gloomy day. Early in the morning, Vladimir Putin announced Russia's intention to invade Ukraine with military forces, claiming their goal was to "demilitarize" the country. Russian troops entered Ukraine through the city of Kharkiv, and the following day they attempted to seize parts of the Ukrainian capital, Kiev (Financial Times, 2023). The invasion led to the worst refugee crisis in Europe since World War II and increased tension across the continent (United Nations, 2022). Since that day, the Swedish economy has continuously weakened. The inflation and interest rates have sharply increased, which has impacted the Swedish stock market (SEB, 2023). Consequently, Russia's invasion of Ukraine has prompted an important and intriguing new area of economic research.

Figure 1: OMXS30 Index

This graph shows OMXS 30 Index for the year 2022.



In times of uncertainty, individuals tend to engage in herding behavior, where they imitate the actions of others to avoid missing out on potential profits (Aharon, 2021). This observation underscores the significance of insider transactions during such periods, and the signaling value they offer. Our paper examines whether insider trading can generate abnormal stock returns in a stable environment, and further explore this phenomenon during uncertain times, such as the period following the invasion of Ukraine on the 24th of February, 2022. Specifically, we investigate whether insider transactions of shares listed on Nasdaq Stockholm can generate an abnormal return between the 4th of July, 2016, and the 31st of December, 2022. Additionally, we investigate whether the Russian invasion of Ukraine has a significant impact on insider trading. We use the event study method by MacKinlay (1997) from the article Event studies in Economics and Finance to answer the following research questions:

*i. Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm?*

*ii. Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm after the invasion of Ukraine?*

Previous studies have generally concurred that insider trading generates an abnormal return in the short run, which challenges the Efficient Market Hypothesis (Fama, 1970). The environment surrounding the stock market has been, and continues to be, undergoing a paradigm shift due to technological advancements. Information can now be disseminated worldwide within seconds, and the entry barriers to the stock market are at an all-time low. Firms today must optimize their reports and press conferences for search engine optimization to signal the well-being of the company due to potential AI interference. Additionally, the Ukraine-Russian relation to the Swedish Stock Market represents an interesting new research area where our analysis can contribute to previous research.

We investigate insider transactions of stocks listed on Nasdaq OMX Stockholm during the period 4th of July, 2016 to the 31st of December, 2022, and examine whether these transactions generate any abnormal returns. Based on the Efficient Market Hypothesis, we expect no information asymmetry in the market, indicating that insider transactions do not generate abnormal returns. However, we anticipate that insider transactions could generate abnormal returns after the Russian invasion of Ukraine due to uncertainty and potential greater signaling values during times of higher volatility.

To conduct our study, we utilize Finansinspektionens's data on insider transactions and employ an event study method inspired by MacKinlay's (1997) methodology. This approach outlines all the necessary steps to define and calculate abnormal returns. We adopt the capital asset pricing model as our normal performance model and select multiple event windows of interest for the study. Additionally, we aggregate the abnormal returns by identifying the difference between the actual and normal return using the cumulative abnormal returns formula for each event window.

We conducted an ordinary least squares regression on the cumulative abnormal return for each event window and ultimately rejected the null hypothesis for the first hypothesis. We find significant abnormal returns that were different from zero by using t-tests for each variable. This suggests that the Efficient Market Hypothesis may not be the prevailing paradigm today (Fama, 1970). However, as with other researchers' findings, the abnormal returns are generally very small.

Based on our analysis, we do not observe enough evidence in all event windows to fully support our second hypothesis. Our results imply that the signaling value of insider trading during times of uncertainty may not be inherently stronger than during more stable market conditions. This phenomenon could be attributed to the existence of greater indicators and parameters that investors can use to evaluate the financial performance of firms, or to the influence of external factors such as inflationary pressures and changes in the repo rate on market trends.

# Theory and Hypothesis

## A. Institutional Framework

The invasion of Ukraine commenced on February 24th, 2022 and has resulted in the tragic loss of thousands of lives. This conflict has a protracted history, beginning in 2014 when Russian forces entered Crimea, a Ukrainian peninsula with a significant population of Russian speakers (Ministry of Foreign Affairs of Ukraine, 2019). Subsequently, Russian troops gained control of the territory, leading to the loss of numerous lives (UK Parliament Commons Library, 2022). Ukraine, a former member of the Soviet Union, is viewed by conservative Russians as a part of their past "glory days," and Crimea is strategically important to Russia due to its positioning with respect to military operations, since Russia lacks a direct shoreline facing Europe. The conflict was unresolved, and eight years later, in 2022, Russian troops once again advanced in eastern Ukraine, leading to a rapid escalation (UK Parliament Commons Library, 2022). The invasion triggered global outrage and created significant apprehension among the general public about what may happen next. In addition to the distressing consequences that inevitably follow during times of war, this invasion has had a profound impact on Europe and its economic system. The invasion served as a catalyst for increased inflation and interest rates. The Swedish capital market experienced an environment characterized by volatility and uncertainty, revealing the close interconnection between the capital market and the real economy (SEB, 2023). During times like this, particularly after the historically high valuations following the Covid-19 period, an event such as this is bound to have an effect on prospective and existing investors in the capital market, where risk management becomes an essential attribute in weighing a portfolio (SEB, 2023). One can imagine that the signaling value (Leland & Pyle, 1977) of insider trading would be of even greater significance during times of high uncertainty since it theoretically implies that insiders believe in the future operations undertaken by the firm. Behavioral effects such as herding (Bikhchandani & Sharma, 2000) may work as a self-fulfilling prophecy, ultimately leading to short-term abnormal returns.

In every publicly traded company, certain individuals hold greater proximity to the decision-making processes than others, such as the CEO, CFO, and board members. These individuals are commonly referred to as insiders, possessing valuable special information concerning the decisions and future performance of their respective companies (Finansinspektionen, 2020). The existence of special information and insider trading seems to contradict the Efficient Market Hypothesis (Fama, 1970), which assumes information symmetry among all investors (Finansinspektionen, 2022). To promote the efficiency of the securities market, insiders are required to report any purchase or disposal of securities to Finansinspektionen (in Sweden), and the information is subsequently published on the regulator's website for public access (Finansinspektionen, 2022).

Numerous studies have explored potential abnormal returns in relation to insider trading, many of which have shown a positive and significant effect on the stock market, this will be addressed further in the literature review. However, the stock market environment has undergone significant changes since the publishing of many papers revolving around insider trading, mainly due to legislative factors such as the Market Abuse Regulation (MAR) from the EU, which aims to address the previously observed information asymmetry (Market Abuse Regulation (19)), and technological advancements, which have made the stock market more widely accessible than ever before (Euroclear, 2021). The general public also has greater access to news feeds, theoretically reducing the “window of opportunity” for insider trading. In addition, many financial firms have incorporated machine learning techniques, which allow them to analyze quarterly reports or perform sentiment analysis during press conferences and other public forums, enabling them to draw conclusions about a company in seconds (Cao, Jiang, Yang, & Zhang, 2020). Overall, the game field has experienced a complete paradigm shift in the past decade, a phenomenon that is likely to have a significant impact on previous research results.

## B. Conditions Affecting the Swedish Stock Market

Today, an increasing number of people in Sweden choose to invest in the stock market for potential future gains. In 2021, there were a total of 2.7 million unique shareholders in Sweden (Euroclear, 2021), accounting for around 26% of the total population. This inevitably makes the Swedish stock market a core pillar in the economic system of Sweden, and it is even more crucial that the system is managed properly and justly. The investors range from students to families with children and retired people who rely on the interest the system can provide for their future pension payments (Euroclear, 2021). Since the group of people who invest in the stock market is very heterogeneous, it is impossible to assume that the core assumption of information symmetry (perfect information) is upheld today. It is possible to argue that Sweden, which has a solid infrastructure and close to nationwide access to the Internet, is closer to a perfect information state than others. However, the problem becomes that of an unequal distribution of knowledge among investors, something that might take the shape of short-term abnormal returns as a reaction to insider trading on a smaller stock market.

To further develop the legitimacy of this paper, we examine how the legislative environment surrounding insider trades and special information has developed over time. As mentioned earlier, numerous papers and extensive research have been published on the topic, particularly in the American stock market. However, very little research has been conducted on how insider trading affects the Swedish stock market. Kallunki’s paper, “Why do insiders trade? Evidence based on unique data on Swedish insiders” (2009), provides evidence that insiders trade for various reasons, such as diversifying their portfolio, but she also connects smaller abnormal returns in an 18-month event-window. Kallunki’s paper is based on insider trades from 197 Swedish firms ranging from 1993 to 2003. At this time, the applicable law regulating insider trading was “Lag (1984:46) om handel med finansiella instrument,” which compelled insiders to disclose any purchases made to Finansinspektionen (FI) to increase transparency and reduce possible fraud and exploitation of common investors in the Swedish stock market. However, as numerous studies have demonstrated, such as Finnerty’s (1976), that insiders are able to identify mispricing of stocks due to their proximity of the core operations, which undermines the paradigm of an effective market, a core assumption of how a well-functioning market works revolving around perfect information.

In 2016, a new law called The Market Abuse Regulation (MAR) was enforced by the European Union to decrease information asymmetry in the financial markets. This law replaced the “Lag (1984:46) om handel med finansiella instrument" in Sweden due to the direct effect the European Union possesses. MAR further restricted and regulated insider trading compared to previous legislation. This enhanced regulation mainly took shape in these ways:

- MAR applies to a wider range of financial instruments, providing greater transparency for outside investors.
- Listed companies are required to issue lists of current insiders and update them frequently. Insiders include people who, in any way, could have access to specific information, such as family members and managers within the firm who have direct contact with decision-makers.
- Companies must disclose any information that could affect the stock market of the company as soon as possible, reducing the time gap of information asymmetry in the stock market.
- MAR increased the sanctions of misuse in the stock market by raising potential fines and imprisonment time (European Union, 2014).

In conclusion, MAR has changed the environment surrounding insider trading by requiring the registration of non-share transactions as well as transactions made by close relatives. This has resulted in over 50,000 registered trades on Nasdaq Stockholm between 2016 and 2022 (Finansinspektionen, 2020). As a result, the previous findings of Kallunki et al. (2009) can not be considered a paradigm for insider trading on the Swedish capital markets anymore.

Another reason why the financial environment has changed can be seen in the research paper "How to Talk When a Machine is Listening?: Corporate Disclosure in the Age of AI" (Cao et al., 2020). Financial reporting has long been recognized as a critical driver of stock price movements, with quarterly expectations playing a pivotal role in shaping market sentiment. Firms that fail to meet market expectations are often penalized by a decline in their stock prices. The authors argue that firms have to adapt their reporting methods in recent times, such as using SEO (search engine optimized) texts and HTML coding that is easy to analyze by potential machine downloading systems. This development reflects the realization by firms that the way they frame their reports could significantly influence their stock price and public perception.

Cao et al. paper suggests that firms have had to adjust their communication methods with their stakeholders because of AI, which is proxied by Machine Downloads. The authors suggest that this creates the following complications by citing Calvano, Calzolari, Denicolo, and Pastorello:

*"While the literature has shown how investors and researchers apply machine learning and computational tools to extract information from disclosure and news, our study is the first to identify and analyze the feedback effect, i.e., how companies adjust the way they talk knowing that machines are listening. Such a feedback effect can lead to unexpected outcomes, such as manipulation and collusion (Calvano et al., 2019)."*

If the feedback effect of Machine Downloads on financial reporting has made firms realize the impact of wording, structure, and sentiment on their overall image, then it may be possible to exploit this knowledge. For example, a press release that is completely search engine optimized can trigger AI to make the firm appear attractive to outsiders. If this occurs multiple times, investors may choose to buy the stock in anticipation of a great quarterly report, leading to a short-term increase in stock price. This is one way of using signaling to convince current stakeholders and potential shareholders that the firm is worth investing in. Another way is to conduct high-volume insider trades between reporting periods. With the sophistication of sentiment analysis and website scraping techniques, there is potential for these systems to exploit other opportunities for arbitrage, such as scraping the registry of insider trades. Given the constant surveillance of publicly available platforms, firms may be tempted to exploit signaling value to their advantage. The financial environment has changed significantly in the past decade due to the rise of technology and the Internet. Consequently, older papers are not necessarily a good benchmark for insider trading consequences in the present-day financial landscape. They may not accurately reflect the truth of today's environment.

## C. Insider Trading and Abnormal Stock Returns

The subject of insider trading and its relationship with excess returns has garnered significant academic attention in recent decades. Moreover, scholars have examined specific subtopics within the domain of insider trading in recent years. In light of the existence of established paradigms surrounding this area, it is essential to differentiate between prior research in this field and how it aligns or conflicts with our research hypotheses and methodology. Hence, this literature review aims to explore how previous papers relate to each other and how our analysis contributes to this research area which will be further discussed in the contribution.

The first part of the Literature Review examines the literature from the past decades that either supports or contradicts the notion that insider trading generates any short term abnormal return. The purpose of this section is to determine whether previous literature supports our hypothesis and how the various conclusions regarding excess return and insider trading have evolved over time.

Insider trading and excess returns have been extensively researched in the literature dating back to 1940 when Smith first addressed this subject. Smith (1940) compared various insider trades and concluded that insider traders may trade for reasons other than potential profit, such as liquidity or diversification. Additionally, Smith (1940) found that insider transactions do not generate significant abnormal returns compared to other investors. However, Jaffe's (1974) and Finnerty's (1976) papers contradict Smith's (1940) perspective and argue that insider traders can use non-public information to make trading decisions and generate excess returns.

Seyhun (1986) further extended this perspective by considering Market Capitalization as a factor affecting the size of abnormal returns and concluded that abnormal returns from insider trades theoretically are greater for transactions in smaller firms than in larger firms. Nevertheless, empirical evidence did not demonstrate a significant correlation between transaction size and abnormal returns from an insider transaction. Furthermore, Seyhun (1986) proposed the Information Hierarchy Hypothesis, suggesting that information asymmetry exists in financial markets, and some investors have more relevant information about stocks than others. This hypothesis is particularly relevant due to the implementation of Market Abuse Regulation (MAR), which categorizes a large number of transactions as insider transactions, even if they are not made by someone who has direct insight into the company.

In contrast to the very nature of abnormal stock returns, Fama (1970) established the Efficient Market Hypothesis, which posits that a market is "informationally efficient" if prices at each moment incorporate all available information about future value. However, Leland and Pyle (1977) found that information asymmetry can create inefficient markets and faulty asset pricing since the general public might not have been informed of all relevant information. Furthermore, Spence (1973) developed a signaling theory, which proposes that employees can use education as a signal for a worker's quality and ability. Although not directly linked to insider trading, insider transactions can potentially serve as a signal to outside investors given the phenomenon of asymmetric information. Leland and Pyle (1977) confirmed the positive signaling effect of insider trading since inside investors have superior information about the company than outsiders possess.

In contrast to the positive signaling effect of insider trading, Lakonishok and Lee (2001) studied the short-term and long-term implications of insider trading and concluded that over a million insider trades did not necessarily generate any abnormal return. This study contradicted previous findings that insider trading should have a positive signaling effect. However, they found a positive correlation between buy transactions within small firms and abnormal returns, which were, on average, very small.

Kallunki et al. (2009) tested the reasoning put forward by Smith (1940) regarding insider trading in the Swedish stock market. Their findings suggest that insiders' trading behavior is driven by factors such as liquidity and diversification, rather than attempting to profit from non-disclosed or privileged information to generate abnormal returns.

## D. Contribution

Most of the research on insider trading and its effects has focused on major stock exchanges such as Nasdaq, the New York Stock Exchange, and the London Stock Exchange. However, what about smaller exchanges, such as Nasdaq Stockholm? There are several factors to consider when comparing the American and Swedish stock markets. First, the American stock market is more mature and has been around for a longer time than the Swedish stock market. Second, the American stock market is more dispersed because there are multiple exchanges, while the Swedish stock market is mainly concentrated around Stockholm OMX. Finally, the American stock market has many more listed companies and a greater volume of investors compared to the Swedish stock market (The World Bank, n.d.). This is not surprising since the US dollar is used as a reserve currency, which attracts many more investors. Additionally, the exchanges have different market regulations, as well as different social and political forces that have a great impact on how the stock market operates.

Furthermore, the environment of the securities market has undergone a complete paradigm shift in the last decade due to technological advancements in the internet and communication channels. These advancements have paved the way for many sophisticated machine-learning algorithms that can potentially shorten the event window like never before.

In summary, there is significantly less relevant contemporary literature about insider trading in Sweden. Furthermore, the ongoing war between Russia and Ukraine has affected the economic system in many ways, leaving us with an unexplored research area of how contemporary insider trading might create abnormal returns on the Swedish Stock Market, even though access to information is greater than ever before.

## E. Hypotheses

This part will first highlight our primary research question and hypothesis. Thereafter, we will present our sub-research question and hypothesis about insider trading and abnormal return characteristics in uncertain times by examining the invasion of Ukraine and its effects on abnormal returns and insider transactions.

The primary hypothesis of this paper revolves around the question of whether there are any short-term abnormal returns after the occurrence of an insider transaction. The conclusions from previous studies conducted have resulted in various outcomes and have moreover revolved around stock exchanges with different characteristics as opposed to Nasdaq Stockholm.

*Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm?*

$$H_0^1 = \mathbf{CAR(t_0,t_n) = 0}$$

$$H_1^1 = \mathbf{CAR(t_0,t_n)} \neq \mathbf{0}$$

This hypothesis will be tested by using the event study approach presented by MacKinlay (1997), focusing on short-term abnormal returns. The method is, by nature, a general approach to examining a hypothesis revolving around an event study but is still to be considered very applicable. The null hypothesis will be that the cumulative abnormal return in a given time period will equal zero, with an alternative hypothesis that it will not equal zero. The reasoning behind this is that we believe that the Efficient Market Hypothesis, along with the mitigating effects on information asymmetry due to the implementation of MAR, should indicate that the status quo of the market is the same as Fama's Efficient market Hypothesis.

Our secondary hypothesis revolves around the characteristics of the volatile environment created by the invasion of Ukraine. The invasion served as a catalyst for a great number of events that came to reshape the real economy as well as the securities market.

*Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm after the invasion of Ukraine?*

$$H_0^2 = \mathbf{CAR(t_0,t_n)} \neq \mathbf{0}$$

$$H_1^2 = \mathbf{CAR(t_0,t_n) = 0}$$

We test this hypothesis by setting out a dummy variable for all dates equal to and above 24th of February 2022. The dummy serves as a control variable. This method looks for any deviations from the mean in regards to the dates that are affected by the invasion of Ukraine. The null hypothesis of this is that the cumulative abnormal return does not equal zero, due to uncertainty and potential signaling in times of higher volatility. The alternative hypothesis is that the cumulative abnormal return equals zero.

# Methodology

## A. Background

The research question of this paper focuses on the potential short-term abnormal returns following an insider transaction and investigates whether such transactions hold greater signaling value during times of high volatility, specifically after the invasion of Ukraine on the 24th of February, 2022.

To address this research question, this paper employs a short-term event study methodology, which draws inspiration from the approach used by MacKinlay (1997). MacKinlay emphasizes that all event studies should follow a similar framework or "flow." Accordingly, this study's initial step is to identify the event of interest and determine the event window, during which the stock prices of the relevant firms will be analyzed. The selection criteria for the sample of firms in the study are then defined. Subsequently, a normal performance model is developed, and the estimation window is established to calculate the abnormal returns using parameter estimates.

The testing framework for abnormal returns is then designed, and important considerations, such as defining the null hypothesis and determining techniques for aggregating individual firm returns, are taken into account. The empirical results are presented based on the formulation of the econometric design.

The purpose of this paper is to assess whether insiders' trades hold signaling value, and this study's methodology provides a general approach for investigating this type of question. By adopting MacKinlay's event study framework, we can ensure a systematic and thorough analysis of the potential abnormal returns associated with insider transactions, specifically in the context of high market volatility following the invasion of Ukraine in 2022.

## B. Short-term Event Study

In accordance with MacKinlay's (1997) recommended methodology, the first step is to select the event and the corresponding event window for the study. In this paper, we focus on insider transactions as the event of interest, and we aim to construct an event window surrounding each transaction. Specifically, the event window will range between seven business days prior to and seven days after the insider transaction. MacKinlay mentions that due to potential information leakage prior to the event of interest it could be of importance to widen the event window backward in time as well:

*"For example, in the earnings announcement case, the market may acquire information about the earnings prior to the actual announcement, and one can investigate this possibility by examining pre-event returns (MacKinlay, 1997)"*

We adopt the methodology proposed by MacKinlay (1997) to ensure a rigorous and unbiased analysis. To establish the event window, we utilize the publishing date from the Swedish Financial Supervisory Authority insider registry as the event of interest (t=0) and set the event window to plus and minus seven business days. This allows us to capture any potential market reactions before and after the insider transaction.

Secondly, the process of MacKinlay (1997) suggests that there should be criteria in how the selection of firms and observations is made. We decide to only include firms listed on Nasdaq Stockholm which is the main stock exchange in Sweden.

The third step involves creating a benchmark for normal returns. To accomplish this, we utilize the market model approach. Specifically, we perform an ordinary least squares (OLS) regression for each firm and respective observations. This enables us to derive a firm-specific beta (slope) and an intercept, which we use to establish normal returns per day.

$$\mathrm{R}_{\mathrm{i,t}} = \alpha_{\mathrm{i}} + \beta_{\mathbf{i}}(\mathrm{R}_{\mathrm{m,t}}) + \epsilon_{\mathbf{i,t}}$$

where:

$\mathrm{R}_{\mathrm{i,t}}$ = Actual Return for given firm in given time period

$\alpha_{\mathrm{i}}$ = Firm specific intercept

$\beta_{\mathrm{i}}$ = Firm specific beta (systematic risk factor)

$\mathrm{R}_{\mathrm{m,t}}$ = The market return in given time period

$\epsilon_{\mathrm{i,t}}$ = Error term

To calculate the normal returns per day, we use a simple linear equation approach:

$$\mathrm{E}(\mathrm{R}_{\mathrm{i,t}}) = \alpha_{\mathrm{i}} + \beta_{\mathbf{i}}(\mathrm{R}_{\mathrm{i,t}})$$

The fourth step of the process refers to the way of calculating the abnormal return of a stock after finding the normal return. The capital asset pricing model refers to the abnormal return as alpha. Therefore our calculation for finding the abnormal return becomes finding alpha in the capital asset pricing model. The equation is defined as follows:

$$\mathrm{AR}_{\mathrm{i,t}} = \mathrm{R}_{\mathrm{i,t}} - \mathrm{E}(\mathrm{R}_{\mathrm{i,t}})$$

where:

$\mathrm{AR}_{\mathrm{i,t}}$ = Abnormal return for given firm in given time period (alpha)

$\mathrm{R}_{\mathrm{i,t}}$ = Actual return for given firm in given time period

$\mathrm{E}(\mathrm{R}_{\mathrm{i,t}})$ = Expected return for given firm in given time period

In the subsequent steps, we aggregate the abnormal returns by employing the cumulative abnormal returns formula for each event window. To elaborate on our approach to determining alpha, we deviate from the conventional method of measuring short-term abnormal returns, namely the cumulative abnormal return formula. Instead, we opt to use the daily fluctuations of stock prices during the event window. To implement this approach, we compute the actual return for a given firm within the designated time period. It is important to note that this method considers day-to-day stock prices rather than referencing the price at $t = 0$. By employing this technique, we are able to pinpoint the exact day when the potential signaling value is reflected in the stock price.

$$R_{i,t} = 1 - \frac{P_{i,t}}{P_{i,t-1}}$$

where:

$P_{i,t}$ = Adjusted close price for time period t

$P_{i,t-1}$ = Adjusted close price for time period t-1

The final step involves cumulating the abnormal returns for each day with t=0 as the benchmark. This step is defined by MacKinlay (1997) as the cumulative abnormal return (CAR) formula, which adds up the abnormal returns from t=0 until the end of the event window. While adding percentages is not an optimal approach, in the case of abnormal returns, which are often very small, it is a reasonable option. However, this method has some limitations. For instance, if a company experiences high volatility during the event window, some CAR results will be above or below 100%. In the case of daily fluctuations, if a company experiences a 50% drop for three days, resulting in a total drop of 87.5%, the CAR at t=3 would be -150%.

$$CAR(t_0, t_n) = \sum_{t=0}^{t=n} AR_{i,t}$$

Ultimately we use OLS regressions to test for significance in the variables to be able to make a conclusion about if and why insider transactions may or may not affect the short-term stock price.

The first regression will be on the entire dataset with the cumulative abnormal returns for each t as a dependent variable.

$$\text{CAR}_{t=n} = \beta_1 \text{ Characteristic} + \beta_2 \text{ Industry} + \beta_3 \text{ MarketCap} + \beta_4 \text{ Year} + \beta_5 \text{ Volume} + \epsilon$$

The second regression covers the entire dataset with the dummy variable War which equals one for every date after the invasion of Ukraine, i.e., all dates after the 24th of February 2022. The rest of the dates have a value of zero. To mitigate the correlation effect between the fixed effect of Year and the War dummy, we remove the Year variable in this regression.

$$\text{CAR}_{t=n} = \beta_1 \text{ War} + \beta_2 \text{ Characteristic} + \beta_3 \text{ Industry} + \beta_4 \text{ MarketCap} + \beta_5 \text{ LogVolume} + \epsilon$$

Figure 2: Definition of Variables

| Variables | Definitions |
|---|---|
| CAR (t) | The dependent variable CAR is defined as Compunded Abnormal Return for each t in the event window. |
| Characterstics | The independent variable Characteristic says whether the transaction is an acquisition or a disposal. |
| Industry | The independent variable Industry controlls for what industry the company operates in. There is eleven different industries in total.* |
| Market Cap | The independent variable Cap controlls for the size of the Company.** |
| Year | The independent variable Year controlls for the year the transaction took place. |
| Volume | The transaction volume of the insider trade expressed in a logarithmic value. |
| War | The dummy variable for the time-dimension of the regression. Expressed as 1 for all dates after 24/02-2022 and 0 if else. |

*Note:*
This figure defines the variables used in our models. *The eleven industries are Basic Material, Consumer Goods, Consumer Services, Energy, Financials, Health Care, Industrials, Real Estate, Technology, Telecommunications and Utilities. **Companies with a market value exceeding EUR 1 billion are in the group of "Large Cap", while companies with a market value between EUR 150 million and EUR 1 billion belong to the "Mid Cap" segment. Companies with a market value smaller than EUR 150 million belong to "Small Cap".

In the fifth and final step, as outlined by MacKinlay, we present the results and discussion section of our paper. In order to ensure the accuracy of our models, we perform a Breusch-Pagan test on each model to detect potential heteroscedasticity, as well as a multicollinearity test. If heteroscedasticity is detected, we create a new model with robust standard errors to compare the results, and if multicollinearity is found, we remove a variable with a value greater than 1.5, which is commonly considered the threshold. Furthermore, we evaluate the t-statistic for all of our coefficients. The t-statistic for an independent variable is frequently used to test the null hypothesis that the coefficient is equal to zero. A significant t-statistic indicates that the variable has explanatory power for the dependent variable. We will calculate this value using the t-statistic formula:

$$t = \frac{\bar{x_i} - \mu_x}{SE(x_i)}$$

where:

$\bar{x_i}$ = Mean of variable

$\mu_x$ = Population mean (assumed to be 0)

$SE(x_i)$ = Standard deviation of variable

# Data

## A. Background

The main goal of a quantitative study is to collect data that can be quantified to derive results from potential correlations between variables. This section will explain the source of the variables, how they were collected, and why they are important to the study. The data was collected between the 4th of January, 2016, until the 31st of December, 2022.

## B. Insider Transactions

The Swedish Financial Supervisory Authority, known as Finansinspektionen (FI), is required by law to publicly disclose every transaction made by an insider. According to the Market Regulatory Act, insiders, along with their family members and individuals closely associated with decision-makers in companies, are obligated to report any transactions they make, including those made with any financial instrument, not just stocks. Finansinspektionen manages the insynsregistret database, which contains all insider transactions that have occurred from 2016 to the present (Finansinspektionen, Insynsregister, 2022). This database is accessible to the public through the insynsregistret website. For our study, we only focus on companies listed on Nasdaq Stockholm. To obtain the necessary data, we manually downloaded all transactions involving these companies from insynsregistret and merged the CSV outputs into a single file using Python.

From the exported CSV files collected, following variables make up the dataset: Publishing date, issuer, a person in a leading position, position, close relative, character, instrument name, instrument type, ISIN, transaction date, volume, volume unit, price, currency, status, and details. The variables used in this study will be publishing date, issuer, character, instrument type, volume, and status. The following section provides the rationale for utilizing the aforementioned variables:

The publication date will serve as the reference point for stock movement in each observation, as this is the moment when the public becomes aware of the transaction and its signaling value. Issuer information will be utilized to match companies with stock prices and assess the effects of insider trade within different industry and Market Capitalization categories. The characteristic will be used as a dummy variable since it provides information as to whether the transaction was an acquisition or disposal. These two serve as opposites in the signaling value of a transaction. The instrument type variable will be utilized to exclude transactions involving instruments other than stocks. The volume variable is analyzed to examine the potential relationship between transaction volume and excess returns. Specifically, a higher volume of shares acquired may reflect confidence in future operations or potential stock movement. Finally, the status variable will be used to filter out revised transactions resulting from registration errors.

## C. Share prices, market indices and risk-free rate

The share price and its volatility after an insider transaction has occurred are of great interest to the study. The daily percentage increase and decrease in the share price of each firm have been collected from Yahoo Finance. To ensure accuracy, the adjusted close price has been used since it reflects the average share price for each day. The data was collected between the 4th of January, 2016 and the 31st of December, 2022, using the yfinance package in Python. For firms with multiple classes of shares, the share price of A-shares was collected as these are most commonly traded by insiders and are more susceptible to the actions of insiders than lower classed shares (Avanza, 2017).

To investigate abnormal returns in the CAPM model (MacKinlay, 1997), the Stockholm OMX30 is used as a market index to replicate market returns. The daily percentage change in the market return has been retrieved from the Nasdaq Sweden website. The data collected for the index changes range between the 4th of January, 2016 and the 31st of December, 2022. The Swedish 10-year government bond yield is used as a risk-free rate and is by nature measured in percentages. The time period for the Swedish 10-year government bond yield data is the same as that of the share price and market index, i.e., the 4th of January, 2016, to the 31st of December, 2022. The data is collected from the Wall Street Journal's database.

Finally, to calculate abnormal returns for given time periods, the beta for each firm needs to be collected. The mean model from MacKinlay (1997) is used to retrieve the firm-specific beta and an intercept.

## D. The ideal dataset

Ideally, we would have used Fama-French factors in our analysis, along with a dataset that included market return and risk-free rate, as well as high minus low (HML) and small minus big (SMB) factors. However, due to limited accessibility, we were unable to obtain a dataset with the necessary dates for Sweden. The Fama-French dataset provided by SSE - Swedish House of Finance only covered up to 2019, which could compromise up to three years of data if used. Additionally, we wanted to examine how the position of insiders affects the signaling value of an insider transaction. However, due to inconsistent reporting, the insider trade registry lacks a standardized way of expressing an insider's position within the company. For instance, CEO can be expressed as "CEO," "Chief Executive Officer," "VD," "Verkställande direktör," or "VD (Verkställande direktör)". This inconsistency was apparent throughout every position in a firm that was considered an insider position. Because of this inconsistency, we decided not to use the variable in our study, even though it may possess explanatory power.

## E. Data filtering

To create a consistent dataset and provide a solid foundation for analyzing the variables, further filtering of the data is necessary. A total of 46,180 insider trades between July 4th, 2016 and February 13th, 2023 were collected from the insider trade registry on the Swedish Financial Supervisory Authority website. Of these, 24920 observations were from Large Cap firms, 13721 from Mid Cap firms, and 6483 from Small Cap firms listed on Nasdaq Stockholm.

i. Firstly, we decide to only use data up until the 31st of December, 2022, as future stock prices are necessary to evaluate movements after insider trade has been published. This resulted in 45305 observations.

ii. Next, we remove transactions that were not an acquisition or disposal (Förvärv/Avyttring), leaving us with 35594 observations.

iii. We also remove non-share transactions, as the signaling value of instruments such as warrants, loans, and dividends is rather insipid, resulting in 32593 observations.

iv. Lastly, we filter out all transactions that have been revised, as these are transactions that have not been accepted due to manual mistakes in reporting. This left us with 30009 observations.

v. Finally, we remove observations with incomplete information (i.e., NA's), resulting in a final dataset of 28019 observations.

Ultimately, we have 28019 observations left between 4th of July 2016 and 31st of December 2022.

# Empirical Results

## A. Distribution of Insider Transactions

The following section provides a summary of the distribution of the insider transactions within the dataset. The tables help you get an initial enhanced understanding of how different sectors might behave with regards to insider trading.

Table 1: Total Number of Insider Transactions

| | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|
| Basic Materials | 1477 | 278 | 142 |
| Consumer Goods | 225 | 418 | 123 |
| Consumer Services | 1362 | 1555 | 611 |
| Energy | 65 | 110 | 41 |
| Financials | 1366 | 801 | 270 |
| Health Care | 776 | 1750 | 1032 |
| Industrials | 5479 | 2016 | 1071 |
| Real Estate | 2052 | 713 | 111 |
| Technology | 1018 | 563 | 731 |
| Telecommunications | 1733 | 46 | 54 |
| Utilities | 0 | 30 | 0 |

*Note:*
This table shows the total amount of insider transactions distributed between the industries. The amount is made up of both acquisitions and disposals between 04/07-2016 up until 31/12-2022. The total number of transactions amounted up to 28019.

Table 2: Total Number of Purchasing/Acquisition Insider Transactions

| | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|
| Basic Materials | 970 | 256 | 107 |
| Consumer Goods | 154 | 348 | 58 |
| Consumer Services | 856 | 1232 | 440 |
| Energy | 44 | 70 | 11 |
| Financials | 991 | 640 | 234 |
| Health Care | 504 | 921 | 881 |
| Industrials | 4352 | 1313 | 858 |
| Real Estate | 1600 | 563 | 81 |
| Technology | 575 | 329 | 551 |
| Telecommunications | 920 | 40 | 32 |
| Utilities | 0 | 23 | 0 |

*Note:*
This table shows the total amount of purchase/acquisition insider transactions distributed between the industries. The amount is made up of only acquisitions between 04/07-2016 up until 31/12-2022. The total number of acquisitions amounted up to 19954.

Table 3: Total Number of Disposal/Sell Insider Transactions

| | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|
| Basic Materials | 507 | 22 | 35 |
| Consumer Goods | 71 | 70 | 65 |
| Consumer Services | 506 | 323 | 171 |
| Energy | 21 | 40 | 30 |
| Financials | 375 | 161 | 36 |
| Health Care | 272 | 829 | 151 |
| Industrials | 1127 | 703 | 213 |
| Real Estate | 452 | 150 | 30 |
| Technology | 443 | 234 | 180 |
| Telecommunications | 813 | 6 | 22 |
| Utilities | 0 | 7 | 0 |

*Note:*
This table shows the total amount of disposal/sell insider transactions distributed between the industries. The amount is made up of only disposals between 04/07-2016 up until 31/12-2022. The total number of disposals amounted up to 8065.

Table 1 displays the total number of insider transactions across Large Cap, Mid Cap, and Small Cap categories within different industries from 2016 to 2022. The data in Table 1 reveals that the industry with the highest number of transactions across all three Market Capitalization categories is Industrials. The second-highest industry is Real Estate. In the Large Cap category, Telecommunications has a significant number of transactions, while in Mid Cap and Small Cap categories, it has few transactions, second-lowest after Utilities. This could be attributed to the industry's structure, where there are few but major players with Market Capitalization of over $10 billion.

Comparing Table 2 and Table 3, we observe that there are more than twice as many acquisitions as disposals, with acquisitions accounting for over 70% of the total transactions. The Industrial and Health Care sectors stand out in both Tables, with a large proportion of transactions across all Market Capitalization categories. As shown in Tables 2 and 3, the data is skewed towards buy transactions (19954) compared to sell transactions (8065). Furthermore, the majority of insider trades originate from Large Cap firms for both acquisitions and disposals, with over 50% of the transactions coming from Large Cap firms in both cases. The Industrial sector has the highest number of observations in both acquisitions (32.5%) and disposals (25.4%). On the other hand, the Utility sector has the least number of observations, with only one company (ARISE) falling into that category.

## B. Descriptive statistics

Table 4 presents summary statistics for the total cumulative abnormal return for t after the event window, including

Table 4: Descriptive Statistics of the Cumulative Abnormal Return Before and After the Publishing of an Insider Transaction

Panel 1: Cumulative Abnormal Return after Publishing of an Insider Transaction

| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
|---|---|---|---|---|---|---|
| Min. | -28.694 | -70.749 | -76.232 | -81.506 | -87.862 | -101.057 |
| 1st Qu. | -1.301 | -1.849 | -2.325 | -2.771 | -3.628 | -4.087 |
| Median | 0.007 | 0.064 | 0.055 | 0.02 | 0.074 | 0.011 |
| Mean | 0.045 | 0.046 | 0.011 | -0.06 | -0.234 | -0.42 |
| 3rd Qu. | 1.378 | 2.093 | 2.467 | 2.825 | 3.411 | 4.051 |
| Max. | 46.378 | 105.529 | 102.036 | 99.217 | 99.967 | 89.211 |

Panel 2: Cumulative Abnormal Return before Publishing of an Insider Transaction

| | t=(-7) | t=(-5) | t=(-3) | t=(-2) | t=(-1) | t=0 |
|---|---|---|---|---|---|---|
| Min. | -101.057 | -95.575 | -68.94 | -61.844 | -50.841 | -28.694 |
| 1st Qu. | -5.338 | -4.432 | -3.471 | -2.651 | -1.983 | -1.301 |
| Median | -0.069 | -0.073 | -0.058 | -0.006 | 0.072 | 0.007 |
| Mean | -0.54 | -0.371 | -0.215 | -0.132 | 0.075 | 0.045 |
| 3rd Qu. | 4.727 | 4.071 | 3.155 | 2.565 | 2.146 | 1.378 |
| Max. | 98.239 | 82.74 | 70.751 | 67.751 | 75.92 | 46.378 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before and after the publishing of an insider transaction. The cumulative abnormal return is not divided into acquisitions and disposals. The statistics is in the timeframe of 04/07-2016 up until 31/12-2022.

both Acquisitions and Disposals. As shown in Tables 2 and 3, there are more acquisitions than disposals. Therefore, the median cumulative abnormal return in Table 4 (panel 1 and panel 2) should be positive, based on the theory of signaling values (Bikhchandani et al, 2000). However, the median cumulative abnormal return in panel 1 is positive but very close to zero, and vice versa for panel 2. Since the median cumulative abnormal return is close to zero in panel 1, it is difficult to conclude any differences in return between the different event windows. However, the fifth-day event window has the highest median return.

Tables 12 to 15 separate all acquisitions for the event window (t=-7 to t=7). From Table 12 (appendix), it can be concluded that the median return decreases when the days from t=0 increase, which is a common observation according to MacKinlay (1997) since a longer event window indicates lower power. Moreover, Table 13 (appendix) shows that the highest average return is at t=(-7), aligning with the theory of MacKinlay. Furthermore, Table 12 (appendix) demonstrates that the cumulative average return from the shorter event windows is less positively skewed than for the larger event windows since the mean cumulative abnormal returns are significantly lower than the median counterpart in the larger event windows.

Table 14 (appendix) presents summary statistics for the cumulative abnormal returns after disposal for every t after the publishing day in percentage. The median abnormal return decreases when the event window becomes larger, and the same pattern is true for the minimum value. However, the maximum value increases as the event window becomes larger. The most significant average abnormal return is one day after the transaction, i.e., when t=1. Table 15 (appendix) presents summary statistics for the cumulative abnormal returns after disposal for every t before the publishing day in percentage. The maximum and minimum value is seven days before the transaction day. The table demonstrates that the mean abnormal return decreases when the event window decreases.

## Table 5: OLS Regression after Publishing of an Insider Transaction

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
| Disposal | **-0.319**$^{***}$ | **-0.096**$^{*}$ | **-0.189**$^{***}$ | **-0.146**$^{*}$ | **-0.259**$^{***}$ | **-0.486**$^{***}$ |
| | (0.042) | (0.058) | (0.071) | (0.081) | (0.098) | (0.109) |
| Consumer Goods | **-0.358**$^{***}$ | -0.240 | -0.279 | -0.343 | **-0.557**$^{*}$ | 0.117 |
| | (0.134) | (0.184) | (0.225) | (0.260) | (0.311) | (0.347) |
| Consumer Services | **-0.175**$^{*}$ | **-0.284**$^{**}$ | **-0.539**$^{***}$ | **-0.627**$^{***}$ | **-1.065**$^{***}$ | **-1.577**$^{***}$ |
| | (0.089) | (0.123) | (0.150) | (0.173) | (0.208) | (0.232) |
| Energy | 0.104 | 0.053 | 0.438 | **0.840**$^{*}$ | 0.463 | 0.791 |
| | (0.223) | (0.307) | (0.375) | (0.432) | (0.518) | (0.577) |
| Financials | -0.057 | **-0.218**$^{*}$ | **-0.427**$^{***}$ | **-0.409**$^{**}$ | **-0.405**$^{*}$ | 0.124 |
| | (0.095) | (0.131) | (0.160) | (0.185) | (0.221) | (0.247) |
| Health Care | 0.006 | 0.192 | 0.124 | 0.205 | 0.177 | **0.419**$^{*}$ |
| | (0.091) | (0.125) | (0.153) | (0.177) | (0.212) | (0.236) |
| Industrials | **-0.131**$^{*}$ | **-0.206**$^{*}$ | **-0.350**$^{***}$ | **-0.435**$^{***}$ | **-0.374**$^{**}$ | -0.114 |
| | (0.079) | (0.109) | (0.133) | (0.154) | (0.184) | (0.205) |
| Real Estate | -0.150 | **-0.219**$^{*}$ | **-0.279**$^{*}$ | -0.099 | -0.014 | 0.303 |
| | (0.092) | (0.126) | (0.154) | (0.178) | (0.213) | (0.237) |
| Technology | -0.004 | **-0.559**$^{***}$ | **-0.613**$^{***}$ | **-0.396**$^{**}$ | **-0.643**$^{***}$ | -0.285 |
| | (0.097) | (0.134) | (0.164) | (0.189) | (0.226) | (0.252) |
| Telecommunications | **0.233**$^{**}$ | **0.821**$^{***}$ | **1.504**$^{***}$ | **1.378**$^{***}$ | **1.517**$^{***}$ | **1.314**$^{***}$ |
| | (0.103) | (0.142) | (0.173) | (0.200) | (0.239) | (0.267) |
| Utilities | -0.663 | -1.085 | **-2.207**$^{**}$ | **-2.563**$^{**}$ | -2.054 | -2.194 |
| | (0.570) | (0.784) | (0.958) | (1.105) | (1.325) | (1.475) |
| Volume (log) | **0.053**$^{***}$ | **0.061**$^{***}$ | **0.084**$^{***}$ | **0.095**$^{***}$ | **0.230**$^{***}$ | **0.252**$^{***}$ |
| | (0.017) | (0.023) | (0.029) | (0.033) | (0.040) | (0.044) |
| Constant | **0.272**$^{**}$ | **0.379**$^{**}$ | **0.530**$^{**}$ | **0.760**$^{***}$ | 0.339 | **0.610**$^{*}$ |
| | (0.123) | (0.170) | (0.208) | (0.239) | (0.287) | (0.320) |
| Fixed effects | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.027 | 0.045 | 0.064 | 0.081 | 0.124 | 0.173 |
| Adjusted $R^2$ | 0.026 | 0.044 | 0.063 | 0.080 | 0.123 | 0.172 |
| Residual Std. Error (df = 27998) | 3.088 | 4.251 | 5.194 | 5.989 | 7.180 | 7.996 |
| F Statistic (df = 20; 27998) | **38.350**$^{***}$ | **65.937**$^{***}$ | **94.936**$^{***}$ | **123.403**$^{***}$ | **197.530**$^{***}$ | **292.095**$^{***}$ |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window after an insider trade has been published. The values are expressed in whole percentages. The table has fixed effects of year and market cap (small/mid/large). The standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

## Table 6: OLS Regression before Publishing of an Insider Transaction

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t= (-7) | t= (-5) | t= (-3) | t= (-2) | t= (-1) | t=0 |
| Disposal | **0.925**$^{***}$ | **0.266**$^{**}$ | **-0.234**$^{**}$ | **-0.547**$^{***}$ | **-0.812**$^{***}$ | **-0.319**$^{***}$ |
| | (0.139) | (0.121) | (0.098) | (0.085) | (0.068) | (0.042) |
| Consumer Goods | 0.375 | -0.434 | **-0.619**$^{**}$ | **-0.549**$^{**}$ | **-0.422**$^{*}$ | **-0.358**$^{***}$ |
| | (0.445) | (0.387) | (0.313) | (0.271) | (0.217) | (0.134) |
| Consumer Services | 0.738$^{**}$ | 0.289 | 0.169 | 0.205 | 0.036 | **-0.175**$^{*}$ |
| | (0.297) | (0.259) | (0.209) | (0.181) | (0.145) | (0.089) |
| Energy | **1.959**$^{***}$ | **1.225**$^{*}$ | 0.516 | 0.733 | 0.419 | 0.104 |
| | (0.741) | (0.644) | (0.522) | (0.451) | (0.361) | (0.223) |
| Financials | 0.164 | -0.252 | -0.123 | 0.030 | **-0.441**$^{***}$ | -0.057 |
| | (0.317) | (0.275) | (0.223) | (0.193) | (0.154) | (0.095) |
| Health Care | -0.019 | -0.326 | 0.169 | **0.587**$^{***}$ | -0.067 | 0.006 |
| | (0.303) | (0.263) | (0.213) | (0.185) | (0.148) | (0.091) |
| Industrials | **0.976**$^{***}$ | **0.379**$^{*}$ | **0.437**$^{**}$ | **0.466**$^{***}$ | -0.109 | **-0.131**$^{*}$ |
| | (0.263) | (0.229) | (0.185) | (0.160) | (0.128) | (0.079) |
| Real Estate | 0.316 | -0.032 | 0.065 | 0.251 | -0.178 | -0.150 |
| | (0.305) | (0.265) | (0.215) | (0.186) | (0.149) | (0.092) |
| Technology | **1.045**$^{***}$ | **1.204**$^{***}$ | **1.388**$^{***}$ | **1.041**$^{***}$ | **0.296**$^{*}$ | -0.004 |
| | (0.323) | (0.281) | (0.228) | (0.197) | (0.158) | (0.097) |
| Telecommunications | **2.282**$^{***}$ | **1.532**$^{***}$ | **1.115**$^{***}$ | **0.289** | **-0.432**$^{***}$ | **0.233**$^{**}$ |
| | (0.342) | (0.298) | (0.241) | (0.209) | (0.167) | (0.103) |
| Utilities | 1.139 | 0.814 | 0.615 | 0.092 | -0.351 | -0.663 |
| | (1.893) | (1.646) | (1.334) | (1.154) | (0.924) | (0.570) |
| Volume (log) | **0.366**$^{***}$ | **0.319**$^{***}$ | **0.404**$^{***}$ | **0.287**$^{***}$ | **0.150**$^{***}$ | **0.053**$^{***}$ |
| | (0.057) | (0.049) | (0.040) | (0.035) | (0.028) | (0.017) |
| Constant | **-0.711**$^{*}$ | -0.217 | **-0.909**$^{***}$ | **-0.770**$^{***}$ | **0.364**$^{*}$ | **0.272**$^{**}$ |
| | (0.410) | (0.357) | (0.289) | (0.250) | (0.200) | (0.123) |
| Fixed effects | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| R$^2$ | 0.135 | 0.100 | 0.075 | 0.066 | 0.043 | 0.027 |
| Adjusted R$^2$ | 0.134 | 0.099 | 0.074 | 0.065 | 0.042 | 0.026 |
| Residual Std. Error (df = 27998) | 10.264 | 8.925 | 7.232 | 6.255 | 5.009 | 3.088 |
| F Statistic (df = 20; 27998) | **218.251**$^{***}$ | **155.687**$^{***}$ | **113.059**$^{***}$ | **98.890**$^{***}$ | **62.910**$^{***}$ | **38.350**$^{***}$ |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window before an insider trade has been published. The values are expressed in whole percentages. The table has fixed effects of year and market cap (small/mid/large). The standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

## C. Distribution of insider transactions before and after the invasion of Ukraine

The following section will provide a summary of the distribution of the data before and after the Russian invasion of Ukraine on the 24th of February, 2022. The tables presented will provide a preliminary understanding of how various sectors may have responded to the invasion.

Table 7: Total Number of Insider Transactions After the Invasion of Ukraine

| | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|
| Basic Materials | 230 | 35 | 20 |
| Consumer Goods | 9 | 51 | 33 |
| Consumer Services | 144 | 296 | 155 |
| Energy | 18 | 19 | 4 |
| Financials | 215 | 141 | 107 |
| Health Care | 123 | 339 | 145 |
| Industrials | 794 | 366 | 200 |
| Real Estate | 371 | 256 | 8 |
| Technology | 264 | 64 | 101 |
| Telecommunications | 456 | 6 | 2 |
| Utilities | 0 | 5 | 0 |

*Note:*
This table shows the total amount of insider transactions distributed between the industries after the invasion of Ukraine on the 24th of February 2022. The amount is made up of both acquisitions and disposals between 04/07-2016 up until 31/12-2022. The total number of transactions amounted up to 4977 with 3716 acquisitions and 1261 disposals

Table 8: Total Number of Insider Transactions Before the Invasion of Ukraine

| | Large Cap | Mid Cap | Small Cap |
|---|---|---|---|
| Basic Materials | 1247 | 243 | 122 |
| Consumer Goods | 216 | 367 | 90 |
| Consumer Services | 1218 | 1259 | 456 |
| Energy | 47 | 91 | 37 |
| Financials | 1151 | 660 | 163 |
| Health Care | 653 | 1411 | 887 |
| Industrials | 4685 | 1650 | 871 |
| Real Estate | 1681 | 457 | 103 |
| Technology | 754 | 499 | 630 |
| Telecommunications | 1277 | 40 | 52 |
| Utilities | 0 | 25 | 0 |

*Note:*
This table shows the total amount of insider transactions distributed between the industries before the invasion of Ukraine on the 24th of February 2022. The amount is made up of both acquisitions and disposals between 04/07-2016 up until 31/12-2022. The total number of transactions amounted up to 23042 with 16238 acquisitions and 6804 disposals

Table 7 indicates that there were no significant changes in the distribution of insider transactions between the two periods compared. Industrials continue to be the industry with the highest number of insider trades in both periods, while Utilities (which only have one company) remain the industry with the lowest number of insider trades. The proportions between acquisitions and disposals also remain similar to those in Table 1. Similarly, Table 8 clearly shows that Large Cap companies have the highest number of insider transactions, while Small Cap companies have the lowest. Overall, there is no significant difference in the distribution of insider transactions between Table 7 and Table 8. However, the rate of transactions per year is slightly higher after the invasion of Ukraine. After the invasion, the rate of transactions per year was around 6000, while before the invasion, it was around 5000.

## D. Descriptive statistics before and after the Invasion of Ukraine

The following section will provide a general overview of the cumulative abnormal returns for each t before and after the invasion.

Table 9: Descriptive Statistics of the Cumulative Abnormal Return Before and After the Invasion of Ukraine

Panel 1: Cumulative Abnormal Return after publishing of an insider transaction

| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
|---|---|---|---|---|---|---|
| Min. | -28.694 | -31.838 | -47.028 | -53.965 | -64.541 | -62.958 |
| 1st Qu. | -2.618 | -4.202 | -5.567 | -7.348 | -10.416 | -13.131 |
| Median | -0.845 | -1.626 | -2.463 | -3.276 | -5.724 | -7.778 |
| Mean | -0.827 | -1.472 | -2.263 | -3.255 | -5.341 | -7.285 |
| 3rd Qu. | 1.2 | 1.129 | 0.916 | 0.539 | -0.06 | -2.251 |
| Max. | 24.352 | 90.525 | 94.239 | 90.537 | 82.218 | 77.383 |

Panel 2: Cumulative Abnormal Return before publishing of an insider transaction

| | t=(-7) | t=(-5) | t=(-3) | t=(-2) | t=(-1) | t=0 |
|---|---|---|---|---|---|---|
| Min. | -90.625 | -72.528 | -62.185 | -61.844 | -45.779 | -28.694 |
| 1st Qu. | -14.742 | -11.183 | -8.036 | -6.945 | -4.93 | -2.618 |
| Median | -8.209 | -6.124 | -4.435 | -3.517 | -1.872 | -0.845 |
| Mean | -8.607 | -6.222 | -3.968 | -3.085 | -1.731 | -0.827 |
| 3rd Qu. | -3.049 | -1.623 | -0.433 | 0.098 | 1.259 | 1.2 |
| Max. | 52.773 | 49.073 | 37.135 | 38.971 | 36.297 | 24.352 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before and after the publishing of an insider transaction. The cumulative abnormal return is not divided into acquisitions and disposals. The statistics is in the timeframe of 24/02-2022 up until 31/12-2022.

Table 9 (panel 1 and 2) show the cumulative abnormal returns after the invasion, i.e., after the 24th of February 2022. The results of these tables show a high mean negative cumulative abnormal return in all event windows where the median for both t=7 and t=(-7) is around 8%. This differs significantly compared to the results in Table 16 (appendix) and 17 (appendix), which show the summary statistics for the cumulative abnormal return before the invasion of Ukraine. These results show that the war has indeed had a significant impact on the stock market as opposed to the time periods before the war, as discussed earlier. In this case, the further away we go from the publishing date (for both acquisitions and disposals), the cumulative abnormal return becomes smaller (greater in absolute terms). Tables 16 and 17 (appendix) provide similar results to Table 4, with the mean hovering around and also increasing in absolute terms the further we move away from the publishing date. The results from Table 9 do not provide a complete picture of how abnormal returns work during periods of high volatility, but rather reflect the effects of the regular performance model chosen. Further discussion on this topic will be presented in the limitations section.

## Table 10: OLS Regression after Publishing of an Insider Transaction with War Dummy

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
| Disposal | **-0.287**$^{***}$ | -0.034 | -0.098 | -0.013 | -0.084 | **-0.236**$^{**}$ |
| | (0.042) | (0.058) | (0.071) | (0.082) | (0.098) | (0.110) |
| War | **-1.081**$^{***}$ | **-1.874**$^{***}$ | **-2.826**$^{***}$ | **-3.947**$^{***}$ | **-6.272**$^{***}$ | **-8.408**$^{***}$ |
| | (0.049) | (0.067) | (0.082) | (0.095) | (0.114) | (0.128) |
| Consumer Goods | **-0.375**$^{***}$ | -0.281 | -0.326 | -0.383 | **-0.634**$^{**}$ | 0.025 |
| | (0.134) | (0.185) | (0.227) | (0.262) | (0.314) | (0.353) |
| Consumer Services | **-0.199**$^{**}$ | **-0.343**$^{***}$ | **-0.616**$^{***}$ | **-0.714**$^{***}$ | **-1.216**$^{***}$ | **-1.781**$^{***}$ |
| | (0.090) | (0.124) | (0.152) | (0.175) | (0.210) | (0.236) |
| Energy | 0.093 | 0.015 | 0.380 | **0.751**$^{*}$ | 0.333 | 0.607 |
| | (0.224) | (0.309) | (0.378) | (0.436) | (0.524) | (0.588) |
| Financials | -0.082 | **-0.265**$^{**}$ | **-0.487**$^{***}$ | **-0.468**$^{**}$ | **-0.523**$^{**}$ | -0.030 |
| | (0.095) | (0.132) | (0.161) | (0.186) | (0.224) | (0.251) |
| Health Care | 0.032 | **0.234**$^{*}$ | 0.183 | 0.279 | 0.258 | **0.518**$^{**}$ |
| | (0.091) | (0.126) | (0.154) | (0.178) | (0.214) | (0.240) |
| Industrials | -0.123 | **-0.201**$^{*}$ | **-0.334**$^{**}$ | **-0.393**$^{**}$ | **-0.340**$^{*}$ | -0.063 |
| | (0.079) | (0.110) | (0.134) | (0.155) | (0.186) | (0.209) |
| Real Estate | -0.147 | -0.202 | -0.243 | -0.025 | 0.103 | **0.460**$^{*}$ |
| | (0.092) | (0.127) | (0.155) | (0.179) | (0.215) | (0.242) |
| Technology | 0.018 | **-0.518**$^{***}$ | **-0.541**$^{***}$ | -0.278 | **-0.460**$^{**}$ | -0.040 |
| | (0.098) | (0.135) | (0.165) | (0.190) | (0.228) | (0.256) |
| Telecommunications | **0.222**$^{**}$ | **0.811**$^{***}$ | **1.491**$^{***}$ | **1.377**$^{***}$ | **1.502**$^{***}$ | **1.292**$^{***}$ |
| | (0.103) | (0.143) | (0.174) | (0.201) | (0.242) | (0.271) |
| Utilities | -0.686 | -1.167 | **-2.341**$^{**}$ | **-2.757**$^{**}$ | **-2.425**$^{*}$ | **-2.679**$^{*}$ |
| | (0.572) | (0.789) | (0.966) | (1.115) | (1.339) | (1.502) |
| Volume (log) | **0.050**$^{***}$ | **0.047**$^{**}$ | **0.061**$^{**}$ | **0.061**$^{*}$ | **0.173**$^{***}$ | **0.174**$^{***}$ |
| | (0.017) | (0.024) | (0.029) | (0.033) | (0.040) | (0.045) |
| Constant | **0.222**$^{**}$ | **0.331**$^{**}$ | **0.488**$^{***}$ | **0.614**$^{***}$ | **0.618**$^{***}$ | **0.739**$^{***}$ |
| | (0.096) | (0.133) | (0.162) | (0.187) | (0.225) | (0.253) |
| Fixed effects | | | | | | |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| R$^2$ | 0.020 | 0.032 | 0.048 | 0.064 | 0.104 | 0.141 |
| Adjusted R$^2$ | 0.019 | 0.031 | 0.047 | 0.063 | 0.103 | 0.141 |
| Residual Std. Error (df = 28003) | 3.099 | 4.280 | 5.236 | 6.045 | 7.261 | 8.146 |
| F Statistic (df = 15; 28003) | **37.163**$^{***}$ | **60.925**$^{***}$ | **93.895**$^{***}$ | **127.115**$^{***}$ | **215.956**$^{***}$ | **306.855**$^{***}$ |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window after an insider trade has been published. The values are expressed in whole percentages. The table has a fixed effect market cap (small/mid/large). The standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

## Table 11: OLS Regression before Publishing of an Insider Transaction with War Dummy

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t= (-7) | t= (-5) | t= (-3) | t= (-2) | t= (-1) | t=0 |
| Disposal | **1.212**$^{***}$ | **0.483**$^{***}$ | -0.082 | **-0.429**$^{***}$ | **-0.743**$^{***}$ | **-0.287**$^{***}$ |
| | (0.140) | (0.121) | (0.099) | (0.085) | (0.068) | (0.042) |
| War | **-9.820**$^{***}$ | **-7.144**$^{***}$ | **-4.583**$^{***}$ | **-3.604**$^{***}$ | **-2.212**$^{***}$ | **-1.081**$^{***}$ |
| | (0.162) | (0.141) | (0.114) | (0.099) | (0.079) | (0.049) |
| Consumer Goods | 0.315 | -0.461 | **-0.633**$^{**}$ | **-0.571**$^{**}$ | **-0.438**$^{**}$ | **-0.375**$^{***}$ |
| | (0.447) | (0.389) | (0.315) | (0.273) | (0.218) | (0.134) |
| Consumer Services | **0.594**$^{**}$ | 0.206 | 0.117 | 0.166 | -0.004 | **-0.199**$^{**}$ |
| | (0.299) | (0.260) | (0.211) | (0.182) | (0.146) | (0.090) |
| Energy | **1.803**$^{**}$ | **1.118**$^{*}$ | 0.444 | 0.685 | 0.386 | 0.093 |
| | (0.745) | (0.648) | (0.525) | (0.455) | (0.363) | (0.224) |
| Financials | 0.083 | -0.292 | -0.159 | -0.007 | **-0.475**$^{***}$ | -0.082 |
| | (0.318) | (0.276) | (0.224) | (0.194) | (0.155) | (0.095) |
| Health Care | 0.115 | -0.208 | 0.275 | **0.704**$^{***}$ | -0.033 | 0.032 |
| | (0.304) | (0.264) | (0.215) | (0.186) | (0.148) | (0.091) |
| Industrials | **1.115**$^{***}$ | **0.506**$^{**}$ | **0.521**$^{***}$ | **0.532**$^{***}$ | -0.083 | -0.123 |
| | (0.265) | (0.230) | (0.186) | (0.161) | (0.129) | (0.079) |
| Real Estate | **0.533**$^{*}$ | 0.131 | 0.142 | 0.295 | -0.151 | -0.147 |
| | (0.306) | (0.266) | (0.216) | (0.187) | (0.149) | (0.092) |
| Technology | **1.351**$^{***}$ | **1.442**$^{***}$ | **1.523**$^{***}$ | **1.140**$^{***}$ | **0.354**$^{**}$ | 0.018 |
| | (0.325) | (0.282) | (0.229) | (0.198) | (0.158) | (0.098) |
| Telecommunications | **2.328**$^{***}$ | **1.560**$^{***}$ | **1.120**$^{***}$ | 0.287 | **-0.445**$^{***}$ | **0.222**$^{**}$ |
| | (0.344) | (0.299) | (0.243) | (0.210) | (0.168) | (0.103) |
| Utilities | 0.761 | 0.562 | 0.498 | 0.017 | -0.417 | -0.686 |
| | (1.905) | (1.655) | (1.343) | (1.162) | (0.928) | (0.572) |
| Volume (log) | **0.298**$^{***}$ | **0.275**$^{***}$ | **0.382**$^{***}$ | **0.275**$^{***}$ | **0.139**$^{***}$ | **0.050**$^{***}$ |
| | (0.057) | (0.049) | (0.040) | (0.035) | (0.028) | (0.017) |
| Constant | **-1.421**$^{***}$ | **-0.875**$^{***}$ | **-1.310**$^{***}$ | **-0.906**$^{***}$ | **0.170** | **0.222**$^{**}$ |
| | (0.320) | (0.278) | (0.226) | (0.195) | (0.156) | (0.096) |
| Fixed effects | | | | | | |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.123 | 0.090 | 0.061 | 0.052 | 0.035 | 0.020 |
| Adjusted $R^2$ | 0.123 | 0.089 | 0.061 | 0.051 | 0.035 | 0.019 |
| Residual Std. Error (df = 28003) | 10.331 | 8.976 | 7.283 | 6.302 | 5.029 | 3.099 |
| F Statistic (df = 15; 28003) | **262.896**$^{***}$ | **183.694**$^{***}$ | **122.209**$^{***}$ | **101.975**$^{***}$ | **67.865**$^{***}$ | **37.163**$^{***}$ |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window before an insider trade has been published. The values are expressed in whole percentages. The table has a fixed effect market cap (small/mid/large). The standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

# Discussion

## A. Test of Hypotheses

In this section, we present the results of our OLS regressions. Firstly, we will examine the OLS regression of the entire dataset spanning from 4th of July 2016 to 31st of December 2022, with a beta derived using the capital asset pricing model. These results will provide a general overview of how insider transactions impact short-term stock returns in the periods before and after the transaction. Secondly, we will investigate the effects of the war and compare the pre- and post-war periods.

For our initial OLS regression, we hypothesized that:

*i. Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm?*

Our null hypothesis was in support of Fama's Efficient Market Hypothesis (Fama, 1970). However, our findings show that the cumulative abnormal return does not equal to zero. To support this hypothesis, tables 5 and 6 should have shown a lack of significance and values around zero. In the regressions, we find multiple instances of significant variables after conducting a t-test. The characteristic variable (which represents whether the transaction is an acquisition or a disposal) showed significance for all event windows, with a percentage decrease of 0.319% (tables 5 and 6) when a disposal transaction was published at t=0. If the Efficient Market Hypothesis were true, the characteristic variable would be 0 or insignificant. However, our models indicate that the characteristic variable is significant in every model, suggesting that there is some explanatory power in an insider trade. Interestingly, there seems to be a shift of signs around three days before an insider trade, indicating that there might be information leakage before the trade.

However, both Table 5 and 6 have a low R-squared, ranging from 0.027 to 0.173, indicating low explanatory power. Despite this, the characteristic variable remains significant, implying that it has some explanatory power for abnormal returns. The volume of the purchase is also positively correlated with insider transactions in all models, indicating that a higher amount of shares bought has a more significant signaling value.

The industries with significant results are mainly Consumer Services and Telecommunications, indicating that these industries are more sensitive to market sentiment than others. However, it is crucial to note that even though all the results in the models are significant, they are very low. The Characteristic variable ranges from 0.925% to -0.486%. These results align somewhat with the findings of Lakonishok & Lee (2001), which stated that there is a significant abnormal return, but it is very low.

Therefore, we reject our null hypothesis of the Efficient Market Hypothesis since our results demonstrate that insider transactions do affect a stock's returns. However, as previously stated, the effect is significant, but not substantial.

Our second hypothesis revolved around the potentially increased signaling value in times of greater volatility - such as the period after the invasion of Ukraine. This period has been characterized by significant fluctuations and high volatility, making it a great time frame to test this hypothesis. Our second hypothesis is:

### *ii. Are there any short-term abnormal returns generated in the given event window after an insider transaction has taken place on Nasdaq Stockholm after the invasion of Ukraine?*

To test the impact of insider trading on stock returns during volatile times, we used a dummy variable to control for all transactions following the invasion and removed the year-fixed effect. Our results indicate that insider trading during turbulent periods affects abnormal returns significantly, as shown in Table 10 and 11. However, the low R-squared values ranging from 0.141 to 0.02 (Table 10 and 11) suggest that insider transactions are not the sole reason for stock price fluctuations, which is not surprising. Notably, the significance of the Characteristic variable is not consistent across all event windows (Table 10), with only the day of publication and seven days later showing a significant effect. The coefficients are also lower than in Table 5. Multicollinearity tests (Table 21) indicate that the War dummy and Characteristic variable do not covariate, suggesting that the War dummy has a more significant actual effect on the abnormal returns than the characteristic variable. Our null hypothesis, that the cumulative abnormal return would not equal zero, is rejected for all t-values, indicating that insider transactions do not necessarily have the same impact during times of high volatility. When considering the War dummy as a control for the characteristic variable, our findings suggest that insider transactions do not necessarily impact stock prices after publication. Interestingly, the time periods before a transaction is made are significant in the majority of the time periods in Table 11, suggesting potential information leakage. Volume is positively correlated in all event windows in Tables 10 and 11, indicating its signaling value. It is important to note that these results have a low R-squared value and low coefficients, similar to the models without the War dummy.

To mitigate the heteroscedasticity problem proven in the testing of the models shown in Table 18 (appendix) and Table 19 (appendix), we also create linear models with robust standard errors as a robustness test for our models. This approach can provide more accurate estimates of the uncertainty in the coefficient estimates when the standard OLS assumptions are violated, as is often the case with low R-squared values and heteroscedasticity. Not surprisingly, the models with robust standard errors generally possess a higher R-squared value, ranging from 0.044 up to 0.305 (Table 23 and 24, appendix) in the models without the War dummy variable. Regarding our first hypothesis, the models with robust standard errors give a somewhat similar result to Table 5 and Table 6 when comparing significance. The time period of the cumulative abnormal return where t=1 is no longer significant, along with t=(-5). As stated earlier, the most remarkable difference is the R-squared of each model, along with some changes in the value of the significant coefficients. These changes are below one percentage for all event windows, which still aligns with the findings of Lakonishok & Lee (2001) and does not necessarily change the outcome. Regarding our second hypothesis, the models with robust standard errors provide results that show a greater R-squared value of the models in general, running between 0.035 to 0.224 (table 24 and 25, appendix). These models also show high significance in the characteristic variable where more time periods are significant. This suggests that insider transactions have an impact on the stock price. However, similar to the previous models, the R-squared of each model is still very low, and the coefficients are still never greater than one percentage unit, suggesting that the effect that insider trading has on stock pricing fluctuations is not very high.

Ultimately, regarding our primary hypothesis, we reject the null hypothesis since the cumulative abnormal return is not equal to 0 after an insider transaction has occurred. With regard to the secondary hypothesis, where the null hypothesis was the opposite of the first one, we find pieces of evidence to reject the null hypothesis. For some event windows, the characteristic variable has a significant effect, considering the war variable as a control where an immediate effect is found (in t=0) and a later effect is found in t=(-7).

## B. Limitations

The OLS regressions revealed that all models had a low level of explanatory power due to the low R-squared value. This suggests that insider trading only partially explains abnormal returns. However, this is expected, given that there are numerous control and binary variables at play. It's not necessarily realistic to expect a high explanatory power with only five variables for a complex event. Additionally, there is often heteroscedasticity present in these models. We conducted Breusch-Pagan tests on all models to check for heteroscedasticity (see Table 18 and 19 in the appendix). The null hypothesis of the Breusch-Pagan test is no heteroscedasticity. If the null hypothesis is rejected, it indicates that there is a missing variable in the model that could explain the fluctuations of the dependent variable (often called omitted variable bias). In our tests, all models rejected the null hypothesis. This suggests that the residuals of each model are correlated and that the model is missing independent variables with higher explanatory power. This is not surprising, given the low R-squared values of each model. To better explain abnormal returns, a more complex model with more variables would be required, as our current models provide a too-simple solution to a highly complex question.

Another limitation of our results is that we used the same normal-performance model beta in every model, implying that market fluctuations are equally high or low in both volatile and less volatile periods. Consequently, the cumulative abnormal return for the War dummy increases significantly the further away from the event we look. During this period, the market experienced a significant drop, resulting in the actual return being much lower than its comparison to the market with a beta derived from less volatile periods. However, creating a new normal performance model using future stock fluctuation is impossible, making it a complex trade-off. As a result, abnormal returns appear to be more significant than they actually are (in absolute terms) compared to the market.

The paper's investigation is limited to insider transactions in Sweden and only uses data from Nasdaq Stockholm. However, this may not provide a complete picture of insider trading in Sweden since there are smaller stock exchanges with different characteristics. Furthermore, the study does not provide evidence on how similar stock exchanges in neighboring countries behave regarding insider transactions. To obtain a more comprehensive understanding of insider trading, the study could have included data from smaller stock exchanges in Sweden and neighboring countries for comparison. In addition, data could have been divided into acquisitions/disposals for more specific results. The paper could have also explored industries with significant results in more depth to understand why some industries may have higher exposure to signaling values on the stock market than others. Finally, investigating long-term stock performance could have been of great interest, assuming insiders buy undervalued stock and sell when overvalued.

# Concluding Remarks

## A. Conclusion

This paper aimed to investigate the link between insider trading and short-term stock returns on the Swedish stock market. The relationship between these two has been a topic of discussion for many decades due to the significant signaling value of insider trades. Prior literature has yielded varying results on whether abnormal returns can be achieved through insider trading and why insiders engage in such transactions. Our study sought to investigate this relationship specifically within the Swedish market, which has seen a gap in research on insider trading since Kallunki et al.'s 2009 paper on why insiders trade in this market. Given the paradigm shifts in capital markets and information technology that have occurred since that time, new research is needed to gain a deeper understanding of the impact of insider trading on short-term stock returns in the Swedish market.

Our study is centered around two hypotheses. The first one explores whether there are any short-term abnormal returns in the Swedish stock market during the periods shortly before and after an insider transaction takes place. The second hypothesis investigates whether the signaling value of insider trading is greater in times of high market volatility, such as during the Russian invasion of Ukraine, compared to less volatile periods. We assumed the Efficient Market Hypothesis by Fama (1970) for the first hypothesis, while the opposite was assumed during periods of high volatility. To examine these relationships, we applied the methodology outlined in MacKinlay's 1997 paper "Event Studies in Economics and Finance."

Regarding our primary hypothesis, we have found compelling evidence that the stock price changes significantly after the publication of an insider transaction, for all event windows following the publishing date. Thus, we reject the null hypothesis, which posits that the cumulative abnormal return is equal to zero in all event windows. Although our results exhibit statistical significance, they are relatively close to zero. Specifically, the coefficient of each event window is below 1% in absolute terms, leading to a similar conclusion as that of Lakonishok and Lee's (2001) study, which revealed that fluctuations after insider transactions are seldom higher than 0.5%.

Our second hypothesis aimed to investigate whether the uncertainty caused by the Russian invasion of Ukraine had an impact on the signaling value of insider trading. We use a dummy variable in the time dimension for the period after the invasion to control for this. Our findings suggest that insider trading does not necessarily lead to higher abnormal stock returns in times of high volatility. Only a few of the event windows became significant when the dummy variable of war was considered a control variable. In the event windows after a transaction had taken place, only the publishing day and seven business days later showed a significant effect different from zero. All significant time periods also had coefficients lower than 1% in absolute terms, which is consistent with the results of Lakonishok and Lee (2001). Thus, we are somewhat unable to reject the null-hypothesis, suggesting that insider transactions do not necessarily relate to higher abnormal stock returns in times of high volatility. The invasion of Ukraine has created a lot of turbulence in the Swedish capital markets and our suggestion would be that there are perhaps better parameters and predictors of future abnormal returns that outside investors take into consideration during times of uncertainty.

There is also a possibility that the general time scope of our model could benefit from being larger, suggesting that insider trading has a long-term signaling value instead of a short-term. Comparing our results with the research of Kallunki et al. (2009) that tangents the subject of abnormal returns on the Swedish we can conclude that our findings align with the underlying point that was made regarding abnormal returns. Kallunki et al. concludes that insider disposals are informative for future abnormal returns. In this paper, a longer event window of 18 months is set up with access to the portfolios of Swedish insiders, but the conclusion remains the same as in our shorter event window. The methods used in Kallunki et al.'s paper could potentially enhance the connection between insider trading and abnormal returns as well as the explanatory power of our models. However, we cannot assume that the stock market is completely efficient even after a shift of paradigm.

As we were investigating abnormal stock returns, we encountered the common issue of heteroscedasticity, along with low explanatory power as evidenced by low R-squared values. To ensure the robustness of our findings, we recreated the models with robust standard errors, but found that this did not significantly alter our results. The models with robust standard errors also demonstrated low explanatory power, with coefficients remaining below 1% in absolute terms. In conclusion, our study has revealed the existence of short-term stock returns in the Swedish stock market in the period following the publication of a transaction. However, we were unable to find any significant relationship between insider trading and abnormal stock returns during periods of high volatility. The reasons for this are unclear, and further research in this area is needed. The study of insider trading, particularly in the context of smaller stock markets such as the Swedish stock exchange, presents many opportunities for future research.

## B. Future Research

Insider trading has been a longstanding topic of interest in the field of finance. Examining its impact on abnormal returns during periods of both stability and volatility has been a subject of discussion among academics worldwide for decades. Financial markets experience periods of volatility, which can result in changes in investor behavior and affect insider trading practices. Exploring the effects of psychological factors on insider trading and excess returns during unstable times, such as the Russia-Ukraine war, is a promising area of research. Investment anxiety, fear, and cognitive biases, like loss aversion, can influence investment decision-making and abnormal returns generated by insider trading during uncertain times. Investigating the behavior of investors in terms of psychological factors and portfolio management could provide valuable insights into the psychology of capital markets globally.

Moreover, conducting a study on neighboring countries' stock markets to Sweden or other smaller stock exchanges could help understand the differences between them. Our research was conducted on a limited sample of Swedish companies listed on Nasdaq Stockholm, and a more comprehensive dataset could provide greater explanatory power to models regarding insider trading. To further explore this topic, a similar study to Kallunki et al. (2009) could be significant in the current environment of the stock market since insider trading has become more complex due to new reporting standards.

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This paper is based on three different types of sources; published papers, government sources and other references. Published papers lay the theoretical foundation for this paper and government and internet sources is used for collecting the data. All references is presented i alphabetical order.

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# Appendix

## Descriptive Statistics

### Acquisitions

Table 12: Descriptive Statistics of the Cumulative Abnormal Return of an Acquisition After Publishing of an Insider Transaction

| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
|---|---|---|---|---|---|---|
| Min. | -28.694 | -70.749 | -76.232 | -81.506 | -87.862 | -101.057 |
| 1st Qu. | -1.250 | -1.893 | -2.407 | -2.878 | -3.763 | -4.247 |
| Median | 0.038 | -0.018 | 0.045 | -0.049 | 0.007 | -0.023 |
| Mean | 0.104 | 0.014 | -0.029 | -0.137 | -0.323 | -0.479 |
| 3rd Qu. | 1.449 | 1.997 | 2.377 | 2.740 | 3.370 | 3.958 |
| Max. | 46.378 | 105.529 | 102.036 | 99.217 | 99.967 | 89.211 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window after the publishing of an acquisition/purchase insider transaction. The cumulative abnormal return is only for the time periods after an acquisition has been made. The statistics is in the timeframe of 04/07-2016 up until 31/12-2022.

Table 13: Descriptive Statistics of the Cumulative Abnormal Return of an Acquisition Before Publishing of an Insider Transaction

| | t=(-7) | t=(-5) | t=(-3) | t=(-2) | t=(-1) | t=0 |
|---|---|---|---|---|---|---|
| Min. | -101.057 | -95.575 | -68.940 | -61.844 | -50.841 | -28.694 |
| 1st Qu. | -5.703 | -4.571 | -3.355 | -2.651 | -1.863 | -1.250 |
| Median | -0.283 | -0.173 | -0.007 | 0.129 | 0.215 | 0.038 |
| Mean | -1.017 | -0.618 | -0.284 | -0.071 | 0.258 | 0.104 |
| 3rd Qu. | 4.506 | 4.071 | 3.136 | 2.730 | 2.251 | 1.449 |
| Max. | 98.239 | 82.740 | 70.751 | 67.751 | 64.497 | 46.378 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before the publishing of an acquisition/purchase insider transaction. The cumulative abnormal return is only for the time periods before an acquisition has been made. The statistics is in the timeframe of 04/07-2016 up until 31/12-2022.

**Disposals**

Table 14: Descriptive Statistics of the Cumulative Abnormal Return of a Disposal After Publishing of an Insider Transaction

| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
|---|---|---|---|---|---|---|
| Min. | -21.576 | -31.838 | -47.028 | -52.345 | -62.147 | -62.827 |
| 1st Qu. | -1.301 | -1.801 | -2.171 | -2.555 | -3.378 | -3.816 |
| Median | -0.083 | 0.233 | 0.086 | 0.134 | 0.243 | 0.107 |
| Mean | -0.100 | 0.124 | 0.111 | 0.132 | -0.016 | -0.273 |
| 3rd Qu. | 1.131 | 2.224 | 2.484 | 3.151 | 3.482 | 4.051 |
| Max. | 33.541 | 38.267 | 71.744 | 99.217 | 63.693 | 82.377 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window after the publishing of an disposal/sell insider transaction. The cumulative abnormal return is only for the time periods after an disposal has been made. The statistics is in the timeframe of 04/07-2016 up until 31/12-2022.

Table 15: Descriptive Statistics of the Cumulative Abnormal Return of a Disposal Before Publishing of an Insider Transaction

| | t=(-7) | t=(-5) | t=(-3) | t=(-2) | t=(-1) | t=0 |
|---|---|---|---|---|---|---|
| Min. | -90.625 | -78.621 | -62.185 | -50.974 | -26.905 | -21.576 |
| 1st Qu. | -4.388 | -4.016 | -3.568 | -2.653 | -2.425 | -1.301 |
| Median | 0.537 | 0.194 | -0.184 | -0.377 | -0.337 | -0.083 |
| Mean | 0.639 | 0.241 | -0.046 | -0.284 | -0.379 | -0.100 |
| 3rd Qu. | 5.315 | 4.171 | 3.211 | 2.122 | 1.678 | 1.131 |
| Max. | 98.239 | 75.642 | 64.135 | 53.998 | 75.920 | 33.541 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before the publishing of an disposal/sell insider transaction. The cumulative abnormal return is only for the time periods before an disposal has been made. The statistics is in the timeframe of 04/07-2016 up until 31/12-2022.

**Before War Period**

Table 16: Descriptive Statistics of the Cumulative Abnormal Return before the Invasion of Ukraine

| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
|---|---|---|---|---|---|---|
| Min. | -27.796 | -70.749 | -76.232 | -81.506 | -87.862 | -101.057 |
| 1st Qu. | -1.043 | -1.417 | -1.663 | -1.869 | -2.227 | -2.563 |
| Median | 0.068 | 0.264 | 0.387 | 0.432 | 0.723 | 0.836 |
| Mean | 0.233 | 0.373 | 0.502 | 0.630 | 0.869 | 1.063 |
| 3rd Qu. | 1.396 | 2.168 | 2.506 | 3.058 | 3.779 | 4.594 |
| Max. | 46.378 | 105.529 | 102.036 | 99.217 | 99.967 | 89.211 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before the invasion of Ukraine. The cumulative abnormal return is made up of both acquisitions and disposals. The statistics is in the timeframe of 04/07-2016 up until 24/02-2022.

Table 17: Descriptive Statistics of the Cumulative Abnormal Return before the Invasion of Ukraine

| | t=(-7) | t=(-5) | t=(-3) | t=(-2) | t=(-1) | t=0 |
|---|---|---|---|---|---|---|
| Min. | -101.057 | -95.575 | -68.940 | -61.755 | -50.841 | -27.796 |
| 1st Qu. | -3.197 | -2.648 | -2.257 | -1.756 | -1.484 | -1.043 |
| Median | 1.172 | 0.771 | 0.464 | 0.392 | 0.344 | 0.068 |
| Mean | 1.202 | 0.893 | 0.595 | 0.506 | 0.465 | 0.233 |
| 3rd Qu. | 5.430 | 4.564 | 3.573 | 2.814 | 2.228 | 1.396 |
| Max. | 98.239 | 82.740 | 70.751 | 67.751 | 75.920 | 46.378 |

*Note:*
This table shows the descriptive statistics for the cumulative abnormal return each event window before the invasion of Ukraine. The cumulative abnormal return is made up of both acquisitions and disposals. The statistics is in the timeframe of 04/07-2016 up until 24/02-2022.

## Model Testing

### Test for heteroscedasticity

Table 18: Breusch-Pagan Test for Heteroscedstacity for Linear Models

| Event | statistic | p.value | parameter | method |
|---|---:|---:|---:|---|
| t=7 | 965.4634 | 0 | 20 | studentized Breusch-Pagan test |
| t=5 | 905.5071 | 0 | 20 | studentized Breusch-Pagan test |
| t=3 | 495.6488 | 0 | 20 | studentized Breusch-Pagan test |
| t=2 | 499.2194 | 0 | 20 | studentized Breusch-Pagan test |
| t=1 | 340.0673 | 0 | 20 | studentized Breusch-Pagan test |
| t=0 | 611.3829 | 0 | 20 | studentized Breusch-Pagan test |
| t=(-1) | 608.8663 | 0 | 20 | studentized Breusch-Pagan test |
| t=(-2) | 1023.8094 | 0 | 20 | studentized Breusch-Pagan test |
| t=(-3) | 1301.2538 | 0 | 20 | studentized Breusch-Pagan test |
| t=(-5) | 1223.6835 | 0 | 20 | studentized Breusch-Pagan test |
| t=(-7) | 1242.3344 | 0 | 20 | studentized Breusch-Pagan test |

*Note:*

This table tests for heterscedasticity for each model/event window. Significant results indicate that the model is subject to heteroscedasticity. A significant result is to be considered a p-value below <0.05.

Table 19: Breusch-Pagan Test for Heteroscedstacity for Linear Models with War Dummy

| Event | statistic | p.value | parameter | method |
|---|---|---|---|---|
| t=7 | 518.6784 | 0 | 15 | studentized Breusch-Pagan test |
| t=5 | 480.0194 | 0 | 15 | studentized Breusch-Pagan test |
| t=3 | 323.7869 | 0 | 15 | studentized Breusch-Pagan test |
| t=2 | 317.1843 | 0 | 15 | studentized Breusch-Pagan test |
| t=1 | 233.5580 | 0 | 15 | studentized Breusch-Pagan test |
| t=0 | 353.4271 | 0 | 15 | studentized Breusch-Pagan test |
| t=(-1) | 477.3391 | 0 | 15 | studentized Breusch-Pagan test |
| t=(-2) | 663.2472 | 0 | 15 | studentized Breusch-Pagan test |
| t=(-3) | 866.3697 | 0 | 15 | studentized Breusch-Pagan test |
| t=(-5) | 769.4267 | 0 | 15 | studentized Breusch-Pagan test |
| t=(-7) | 796.5696 | 0 | 15 | studentized Breusch-Pagan test |

*Note:*

This table tests for heterscedasticity for each model/event window with the war dummy. Significant results indicate that the model is subject to heteroscedasticity. A significant result is to be considered a p-value below <0.05.

### Multicollinearity test

Table 20: Multicollinearity Test for Linear Models

| | GVIF | Df | GVIF^(1/(2*Df)) |
|---|---|---|---|
| Characteristic | 1.059402 | 1 | 1.029273 |
| Industry | 1.387404 | 10 | 1.016506 |
| Cap | 1.253665 | 2 | 1.058145 |
| Year | 1.048009 | 6 | 1.003915 |
| Log_Volume | 1.112588 | 1 | 1.054793 |

*Note:*
This table tests for multicollinearity for the linear models. Significant results indicate that the variable is subject to multicollinearity. A significant result is to be considered a GVIF value equal to or over >1.5.

Table 21: Multicollinearity Test for Linear Models with War Dummy

| | GVIF | Df | GVIF^(1/(2*Df)) |
|---|---|---|---|
| Characteristic | 1.052191 | 1 | 1.025764 |
| War | 1.009668 | 1 | 1.004822 |
| Industry | 1.353902 | 10 | 1.015265 |
| Cap | 1.252001 | 2 | 1.057794 |
| Log_Volume | 1.106487 | 1 | 1.051897 |

*Note:*
This table tests for multicollinearity for the linear models with the war dummy. Significant results indicate that the variable is subject to multicollinearity. A significant result is to be considered a GVIF value equal to or over >1.5.

## Table 22: OLS Regression after Publishing of an Insider Transaction with Robust Standard Errors

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
| Disposal | **-0.252**$^{***}$ | 0.043 | **-0.183**$^{***}$ | **-0.221**$^{***}$ | **-0.340**$^{***}$ | **-0.418**$^{***}$ |
| | (0.029) | (0.042) | (0.052) | (0.059) | (0.073) | (0.081) |
| Consumer Goods | **-0.321**$^{***}$ | **-0.382**$^{***}$ | **-0.554**$^{***}$ | **-0.722**$^{***}$ | **-0.911**$^{***}$ | **-0.547**$^{***}$ |
| | (0.080) | (0.108) | (0.132) | (0.145) | (0.171) | (0.200) |
| Consumer Services | -0.061 | **-0.252**$^{***}$ | **-0.442**$^{***}$ | **-0.513**$^{***}$ | **-0.584**$^{***}$ | **-0.518**$^{***}$ |
| | (0.067) | (0.090) | (0.116) | (0.130) | (0.156) | (0.181) |
| Energy | 0.132 | -0.160 | **-0.503**$^{*}$ | -0.154 | 0.064 | 0.057 |
| | (0.171) | (0.258) | (0.302) | (0.372) | (0.452) | (0.533) |
| Financials | 0.006 | -0.057 | **-0.254**$^{**}$ | **-0.243**$^{*}$ | -0.230 | 0.078 |
| | (0.067) | (0.092) | (0.113) | (0.128) | (0.153) | (0.177) |
| Health Care | -0.090 | 0.084 | -0.090 | 0.027 | -0.198 | -0.007 |
| | (0.069) | (0.092) | (0.116) | (0.132) | (0.158) | (0.184) |
| Industrials | -0.005 | -0.057 | **-0.248**$^{***}$ | **-0.366**$^{***}$ | **-0.329**$^{***}$ | -0.124 |
| | (0.057) | (0.076) | (0.095) | (0.108) | (0.127) | (0.150) |
| Real Estate | 0.037 | 0.035 | 0.064 | 0.172 | **0.316**$^{**}$ | **0.746**$^{***}$ |
| | (0.065) | (0.088) | (0.108) | (0.125) | (0.149) | (0.176) |
| Technology | 0.037 | **-0.754**$^{***}$ | **-0.901**$^{***}$ | **-0.753**$^{***}$ | **-1.222**$^{***}$ | **-0.878**$^{***}$ |
| | (0.075) | (0.114) | (0.134) | (0.145) | (0.173) | (0.192) |
| Telecommunications | **0.366**$^{***}$ | **0.896**$^{***}$ | **0.987**$^{***}$ | **0.744**$^{***}$ | **1.248**$^{***}$ | **1.267**$^{***}$ |
| | (0.076) | (0.109) | (0.142) | (0.167) | (0.200) | (0.213) |
| Utilities | -0.642 | **-0.874**$^{*}$ | **-1.865**$^{**}$ | **-1.988**$^{***}$ | **-3.504**$^{***}$ | **-4.003**$^{***}$ |
| | (0.393) | (0.449) | (0.783) | (0.758) | (0.856) | (0.852) |
| Volume (log) | **0.043**$^{***}$ | 0.020 | **0.034**$^{*}$ | 0.021 | **0.128**$^{***}$ | **0.129**$^{***}$ |
| | (0.012) | (0.016) | (0.020) | (0.023) | (0.029) | (0.032) |
| Constant | **0.239**$^{***}$ | **0.360**$^{***}$ | **0.624**$^{***}$ | **1.034**$^{***}$ | **0.617**$^{***}$ | **0.636**$^{***}$ |
| | (0.080) | (0.107) | (0.132) | (0.151) | (0.184) | (0.207) |
| Fixed effects | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.044 | 0.087 | 0.128 | 0.153 | 0.229 | 0.305 |
| Adjusted $R^2$ | 0.043 | 0.086 | 0.127 | 0.152 | 0.228 | 0.304 |
| Residual Std. Error (df = 27998) | 1.954 | 2.801 | 3.336 | 3.832 | 4.681 | 5.295 |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window after an insider trade has been published. The values are expressed in whole percentages. The table has fixed effects of year and market cap (small/mid/large). The robust standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

## Table 23: OLS Regression before Publishing of an Insider Transaction with Robust Standard Errors

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t= (-7) | t= (-5) | t= (-3) | t= (-2) | t= (-1) | t=0 |
| Disposal | **0.392**$^{***}$ | -0.132 | **-0.568**$^{***}$ | **-0.736**$^{***}$ | **-0.854**$^{***}$ | **-0.252**$^{***}$ |
| | (0.098) | (0.085) | (0.063) | (0.052) | (0.045) | (0.029) |
| Consumer Goods | **1.028**$^{***}$ | 0.175 | -0.227 | **-0.524**$^{***}$ | **-0.525**$^{***}$ | **-0.321**$^{***}$ |
| | (0.286) | (0.240) | (0.189) | (0.156) | (0.113) | (0.080) |
| Consumer Services | **1.047**$^{***}$ | **0.475**$^{***}$ | **0.321**$^{**}$ | **0.324**$^{***}$ | -0.078 | -0.061 |
| | (0.215) | (0.178) | (0.141) | (0.119) | (0.092) | (0.067) |
| Energy | **1.999**$^{***}$ | **1.062**$^{**}$ | **0.820**$^{*}$ | 0.388 | 0.221 | 0.132 |
| | (0.638) | (0.540) | (0.462) | (0.346) | (0.248) | (0.171) |
| Financials | **0.634**$^{***}$ | 0.099 | -0.041 | 0.071 | **-0.404**$^{***}$ | 0.006 |
| | (0.210) | (0.175) | (0.142) | (0.120) | (0.094) | (0.067) |
| Health Care | **0.625**$^{***}$ | 0.208 | **0.270**$^{*}$ | **0.533**$^{***}$ | **-0.171**$^{*}$ | -0.090 |
| | (0.229) | (0.201) | (0.153) | (0.126) | (0.103) | (0.069) |
| Industrials | **1.574**$^{***}$ | **0.782**$^{***}$ | **0.744**$^{***}$ | **0.565**$^{***}$ | -0.104 | -0.005 |
| | (0.161) | (0.133) | (0.111) | (0.097) | (0.077) | (0.057) |
| Real Estate | **1.474**$^{***}$ | **0.806**$^{***}$ | **0.577**$^{***}$ | **0.488**$^{***}$ | -0.121 | 0.037 |
| | (0.188) | (0.162) | (0.132) | (0.116) | (0.093) | (0.065) |
| Technology | **1.295**$^{***}$ | **0.918**$^{***}$ | **0.602**$^{***}$ | **0.468**$^{***}$ | 0.086 | 0.037 |
| | (0.255) | (0.205) | (0.151) | (0.132) | (0.112) | (0.075) |
| Telecommunications | **2.170**$^{***}$ | **1.389**$^{***}$ | **0.906**$^{***}$ | -0.072 | **-0.731**$^{***}$ | **0.366**$^{***}$ |
| | (0.198) | (0.168) | (0.139) | (0.122) | (0.110) | (0.076) |
| Utilities | **2.094**$^{***}$ | **1.529**$^{*}$ | **1.092**$^{**}$ | 0.312 | -0.329 | -0.642 |
| | (0.726) | (0.801) | (0.537) | (0.523) | (0.553) | (0.393) |
| Volume (log) | **0.275**$^{***}$ | **0.259**$^{***}$ | **0.303**$^{***}$ | **0.204**$^{***}$ | **0.143**$^{***}$ | **0.043**$^{***}$ |
| | (0.040) | (0.035) | (0.026) | (0.022) | (0.018) | (0.012) |
| Constant | **-0.729**$^{***}$ | -0.303 | **-0.593**$^{***}$ | **-0.448**$^{***}$ | **0.490**$^{***}$ | **0.239**$^{***}$ |
| | (0.241) | (0.206) | (0.168) | (0.142) | (0.114) | (0.080) |
| Fixed effects | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.264 | 0.213 | 0.167 | 0.160 | 0.095 | 0.044 |
| Adjusted $R^2$ | 0.264 | 0.213 | 0.167 | 0.159 | 0.095 | 0.043 |
| Residual Std. Error (df = 27998) | 6.401 | 5.442 | 4.353 | 3.623 | 2.974 | 1.954 |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window before an insider trade has been published. The values are expressed in whole percentages. The table has fixed effects of year and market cap (small/mid/large). The robust standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

### Table 24: OLS Regression after Publishing of an Insider Transaction with War Dummy and RSE

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=2 | t=3 | t=5 | t=7 |
| Disposal | **-0.229**$^{***}$ | **0.115**$^{***}$ | -0.058 | -0.052 | **-0.137**$^{*}$ | **-0.175**$^{**}$ |
| | (0.029) | (0.042) | (0.053) | (0.060) | (0.075) | (0.086) |
| War | **-0.912**$^{***}$ | **-1.777**$^{***}$ | **-2.802**$^{***}$ | **-3.902**$^{***}$ | **-6.204**$^{***}$ | **-8.564**$^{***}$ |
| | (0.044) | (0.066) | (0.083) | (0.099) | (0.123) | (0.135) |
| Consumer Goods | **-0.360**$^{***}$ | **-0.447**$^{***}$ | **-0.663**$^{***}$ | **-0.829**$^{***}$ | **-0.998**$^{***}$ | **-0.710**$^{***}$ |
| | (0.080) | (0.109) | (0.133) | (0.150) | (0.180) | (0.220) |
| Consumer Services | -0.097 | **-0.339**$^{***}$ | **-0.615**$^{***}$ | **-0.665**$^{***}$ | **-0.886**$^{***}$ | **-1.001**$^{***}$ |
| | (0.067) | (0.091) | (0.115) | (0.129) | (0.156) | (0.183) |
| Energy | 0.099 | -0.207 | **-0.658**$^{**}$ | -0.288 | -0.145 | -0.156 |
| | (0.169) | (0.267) | (0.304) | (0.367) | (0.461) | (0.537) |
| Financials | -0.025 | -0.130 | **-0.421**$^{***}$ | **-0.433**$^{***}$ | **-0.505**$^{***}$ | -0.279 |
| | (0.067) | (0.091) | (0.113) | (0.129) | (0.155) | (0.180) |
| Health Care | -0.088 | 0.105 | -0.093 | 0.064 | -0.131 | 0.066 |
| | (0.069) | (0.093) | (0.116) | (0.133) | (0.161) | (0.189) |
| Industrials | -0.016 | -0.095 | **-0.301**$^{***}$ | **-0.390**$^{***}$ | **-0.368**$^{***}$ | -0.173 |
| | (0.057) | (0.075) | (0.094) | (0.107) | (0.127) | (0.149) |
| Real Estate | 0.033 | 0.014 | -0.003 | 0.134 | **0.284**$^{*}$ | **0.690**$^{***}$ |
| | (0.065) | (0.088) | (0.109) | (0.125) | (0.152) | (0.180) |
| Technology | 0.049 | **-0.728**$^{***}$ | **-0.886**$^{***}$ | **-0.689**$^{***}$ | **-1.083**$^{***}$ | **-0.647**$^{***}$ |
| | (0.076) | (0.116) | (0.136) | (0.147) | (0.180) | (0.201) |
| Telecommunications | **0.370**$^{***}$ | **0.904**$^{***}$ | **1.021**$^{***}$ | **0.808**$^{***}$ | **1.275**$^{***}$ | **1.247**$^{***}$ |
| | (0.076) | (0.109) | (0.140) | (0.163) | (0.196) | (0.215) |
| Utilities | **-0.693**$^{*}$ | **-1.030**$^{**}$ | **-2.141**$^{***}$ | **-2.226**$^{***}$ | **-3.985**$^{***}$ | **-4.954**$^{***}$ |
| | (0.388) | (0.425) | (0.798) | (0.799) | (0.828) | (0.845) |
| Volume (log) | **0.033**$^{***}$ | -0.005 | 0.002 | -0.016 | **0.069**$^{**}$ | 0.051 |
| | (0.012) | (0.017) | (0.020) | (0.023) | (0.030) | (0.034) |
| Constant | **0.217**$^{***}$ | **0.395**$^{***}$ | **0.700**$^{***}$ | **0.863**$^{***}$ | **0.871**$^{***}$ | **0.993**$^{***}$ |
| | (0.070) | (0.093) | (0.116) | (0.131) | (0.161) | (0.183) |
| Fixed effects | | | | | | |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.035 | 0.058 | 0.086 | 0.115 | 0.169 | 0.224 |
| Adjusted $R^2$ | 0.035 | 0.058 | 0.086 | 0.114 | 0.169 | 0.223 |
| Residual Std. Error (df = 28003) | 1.964 | 2.853 | 3.452 | 3.973 | 4.969 | 5.726 |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window after an insider trade has been published. The values are expressed in whole percentages. The table has a fixed effect market cap (small/mid/large). The robust standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).

### Table 25: OLS Regression before Publishing of an Insider Transaction with War Dummy and RSE

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | t= (-7) | t= (-5) | t= (-3) | t= (-2) | t= (-1) | t=0 |
| Disposal | **0.640**$^{***}$ | 0.066 | **-0.405**$^{***}$ | **-0.613**$^{***}$ | **-0.796**$^{***}$ | **0.229**$^{***}$ |
| | (0.103) | (0.088) | (0.064) | (0.053) | (0.045) | (0.029) |
| War | **-9.941**$^{***}$ | **-7.381**$^{***}$ | **-4.901**$^{***}$ | **-3.909**$^{***}$ | **-2.233**$^{***}$ | **0.912**$^{***}$ |
| | (0.153) | (0.126) | (0.095) | (0.081) | (0.072) | (0.044) |
| Consumer Goods | **0.788**$^{***}$ | 0.116 | -0.257 | **-0.514**$^{***}$ | **-0.551**$^{***}$ | **0.360**$^{***}$ |
| | (0.302) | (0.255) | (0.196) | (0.160) | (0.114) | (0.080) |
| Consumer Services | **0.687**$^{***}$ | 0.288 | **0.287**$^{**}$ | **0.307**$^{**}$ | -0.120 | -0.097 |
| | (0.224) | (0.186) | (0.144) | (0.120) | (0.093) | (0.067) |
| Energy | **1.535**$^{**}$ | 0.787 | **0.883**$^{*}$ | 0.449 | 0.200 | 0.099 |
| | (0.662) | (0.574) | (0.485) | (0.352) | (0.251) | (0.169) |
| Financials | **0.371**$^{*}$ | -0.110 | -0.140 | 0.012 | **-0.455**$^{***}$ | -0.025 |
| | (0.221) | (0.183) | (0.145) | (0.122) | (0.095) | (0.067) |
| Health Care | **0.566**$^{**}$ | 0.165 | **0.346**$^{**}$ | **0.664**$^{***}$ | **-0.171**$^{*}$ | -0.088 |
| | (0.236) | (0.206) | (0.153) | (0.126) | (0.103) | (0.069) |
| Industrials | **1.590**$^{***}$ | **0.864**$^{***}$ | **0.802**$^{***}$ | **0.637**$^{***}$ | -0.102 | -0.016 |
| | (0.173) | (0.139) | (0.112) | (0.098) | (0.077) | (0.057) |
| Real Estate | **1.482**$^{***}$ | **0.847**$^{***}$ | **0.638**$^{***}$ | **0.547**$^{***}$ | -0.113 | 0.033 |
| | (0.200) | (0.169) | (0.135) | (0.118) | (0.094) | (0.065) |
| Technology | **1.513**$^{***}$ | **1.210**$^{***}$ | **0.815**$^{***}$ | **0.620**$^{***}$ | 0.143 | 0.049 |
| | (0.265) | (0.213) | (0.153) | (0.133) | (0.112) | (0.076) |
| Telecommunications | **2.442**$^{***}$ | **1.610**$^{***}$ | **1.005**$^{***}$ | 0.030 | **-0.687**$^{***}$ | **0.370**$^{***}$ |
| | (0.214) | (0.177) | (0.143) | (0.124) | (0.110) | (0.076) |
| Utilities | 1.424$^{*}$ | 1.142 | 0.882 | 0.185 | -0.429 | -0.693$^{*}$ |
| | (0.739) | (0.801) | (0.538) | (0.537) | (0.563) | (0.388) |
| Volume (log) | **0.196**$^{***}$ | **0.206**$^{***}$ | **0.265**$^{***}$ | **0.177**$^{***}$ | **0.126**$^{***}$ | **0.033**$^{***}$ |
| | (0.041) | (0.035) | (0.026) | (0.022) | (0.018) | (0.012) |
| Constant | **-0.970**$^{***}$ | **-0.455**$^{**}$ | **-0.709**$^{***}$ | **-0.377**$^{***}$ | **0.357**$^{***}$ | **0.217**$^{***}$ |
| | (0.216) | (0.179) | (0.139) | (0.120) | (0.096) | (0.070) |
| Fixed effects | | | | | | |
| Market Cap | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 | 28,019 |
| $R^2$ | 0.215 | 0.173 | 0.138 | 0.133 | 0.079 | 0.035 |
| Adjusted $R^2$ | 0.215 | 0.173 | 0.137 | 0.133 | 0.079 | 0.035 |
| Residual Std. Error (df = 28003) | 6.855 | 5.722 | 4.542 | 3.723 | 3.042 | 1.964 |

This table shows the OLS regression for the general dataset covering insider trades between 04/07-2016 up to 31/12-2022. The columns are made up of each event window before an insider trade has been published. The values are expressed in whole percentages. The table has a fixed effect market cap (small/mid/large). The robust standard errors are made expressed in parenthesises below the coefficients. The significance of the coefficients is calculated by using a t-test and significance is shown in asterixis ($^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01).