THE IMPACT OF STOCK MARKET MANIPULATION

AN EMPIRICAL STUDY OF NASDAQ STOCKHOLM STOCK EXCHANGE DURING 2018-2023

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Abstract:

Despite widespread concern about market manipulation, there is a general lack of empirical evidence in the literature to support this claim. In particular, market manipulation has not been thoroughly investigated in advanced stock markets. To fill this gap, this study is empirically examining the impact of stock market manipulation on market quality on the Nasdaq Stockholm stock exchange. The objective is to study whether manipulation distorts the market, both during and after the manipulation. The empirical study uses 31 prosecuted manipulation cases between 2018 and 2023 and discovers several effects of manipulation that align with market microstructure theory. The study finds the bid-ask spread widened in response to manipulation, which could cause rational investors to exit the market to avoid trading with a manipulator. These findings suggest that market manipulation is harmful to information-seeking investors, who typically maintain markets efficient. Moreover, the study finds that manipulators can execute large, profitable trades, challenging the theory that trade size serves as a proxy for information asymmetry. The study also shows that the illiquidity ratio is not significantly affected by market manipulation. The findings are showing that manipulation on the Stockholm stock exchange is exposed a significant level of inefficiency, making it challenging to maintain fair pricing. The results also support earlier studies that stocks with low liquidity and volume are more prone to manipulation.

Keywords:

Stock Manipulation, Market Efficiency, Market Quality, Stockholm stock exchange, Market microstructure

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1. Introduction

Providing effective trading facilities for market participants is crucial for enabling seamless trading of listed securities (Gao & Kling, 2006). A well-developed stock exchange is expected to increase savings by making a wide range of financial securities available to savers (Boubakari & Jin, 2010). Such diversification of savers' portfolios helps reduce risk and effectively allocate capital to the most productive units of the economy, resulting in efficient capital allocation. However, the existence of stock market manipulation is a significant problem that hinders stock markets from fulfilling this crucial role (Aggarwal & Wu, 2006). Concerns about market manipulation have steadily grown over the last two decades (eg. Aggarwal & Wu, 2006; Comerton-Forde & Putnins, 2011; Gao & Oler, 2012; Chow et al, 2013; Qi et al, 2014) and it is regarded as a significant issue for trade regulation and market efficiency. Market manipulation is a major concern because it harms individual investors, undermines confidence in market integrity, and reduces overall market efficiency (Gerace et al, 2014). Despite the concerns about market manipulation, empirical evidence to support this issue is lacking in the literature. The purpose of this thesis is to fill this gap in the literature by empirically investigating the impact of stock market manipulation on market quality on the Nasdaq Stockholm stock exchange.

Understanding the impact of stock market manipulation on market quality is important for several reasons. First, fair pricing and efficient markets. Market manipulators use various schemes to disrupt the free and fair operation of the market, with the goal of profiting from stock price fluctuations (Allen & Gale, 1992). Manipulation can thus distort security prices, create volatility, and affect the bid-ask spreads (Aggarwal & Wu, 2006). Second, market manipulation can have a negative impact on economic growth. Economic variables such as GDP have been found to react negatively to manipulative trading (Akinmade et al, 2020). Third, policy and regulatory efforts. With the rapid development in society in terms of technology and accessibility, many countries and stock exchanges, particularly in advanced economies, have implemented stricter legislation to protect investors, increase market transparency, and improve the functioning of financial markets. Empirical evidence is therefore essential to guide these efforts. Last, academic research is limited. There are only a few empirical studies of market manipulation, particularly those that investigate how manipulative trading affects the stock market quality (Akinmade et al, 2020). Only three other studies, that we are aware of, empirically investigate manipulation and its impact on market quality. Aggarwal and Wu (2006) studied cases in the United States, whereas Gerace et al (2014) and Akinmade et al (2020) concentrated on the less developed stock markets of Hong Kong and Nigeria. An extensive literature search reveals that Sweden, an advanced market, and the Swedish stock exchange have not been studied in-depth.

Therefore, more empirical research on market quality and manipulation is needed. For these reasons, we have chosen to study the following research question:

What impact does stock market manipulation have on market quality on the Stockholm stock exchange?

This thesis explores three dimensions to examine the effects of stock market manipulation. First, the price dimension. Here we refer to the price of liquidity that captures the cost of trading in securities and trading frictions in the market. The price of liquidity is often measured by the bid-ask spread. A high level of liquidity in the stock market is essential for market efficiency, but information asymmetry can give some investors an advantage over others in terms of knowledge. When a manipulator spreads false information that is perceived as "private information," they can profit by trading against investors seeking accurate information (Kim & Park, 2010). The rational, information-seeking investors may then demand a wider bid-ask spread to compensate for the risk of trading with a manipulator, raising the price of liquidity and resulting in a less effective market (Kyle, 1985). Consequently, market manipulation is expected to increase the bid-ask spread, reflecting rational investors' concerns. Second, the quantity dimension. As with the price dimension, rational investors reduce the depth of their trade to avoid trading with a manipulator, suggesting that large trades are subject to adverse selection risk (Easley & O'Hara, 1987). Manipulation is therefore expected to decrease the trading volume of a stock. Third, the illiquidity dimension. To investigate illiquidity, we use stock price reactions to order flows as a proxy for market breadth. This is based on the idea that when illiquidity is high, large quantity transactions have a greater impact on the stock price. Given the expected effects of manipulation on the spread and trade volume, market manipulation is expected to increase a stock's illiquidity. Furthermore, as manipulators seek to profit from stock price fluctuations, existing literature has found an increased likelihood of successful manipulation in stocks with low liquidity and low trading volume (Thel, 1994; Aggarwal & Wu, 2006). These findings are expected to be confirmed in our study.

The investigation starts by shedding light on descriptive statistics of specific market quality measures such as proportional bid-ask spread, volume, volatility, share turnover, and illiquidity. This is done through univariate analysis where we compare the descriptive statistics of the pre-manipulation and post-manipulation periods. The univariate findings suggest that the spreads, returns, liquidity, volatility, and trading volume are all affected by market manipulation. Similarly, all the measures were found to increase in the post-manipulation period compared to the pre-manipulation period.

Then, we perform three sets of regression analyses to test our three dimensions to further investigate the relationship between the variables. Our results suggest that rational investors might exit the market to avoid trading with a manipulator. Consequently, our analysis shows that manipulation on the Stockholm stock exchange is exposed a significant level of inefficiency. However, the results indicate that there is no substantiation to support the theory that larger trades are executed at unfavorable prices. This study reveals that apart from smaller trades, manipulators can execute large, profitable trades. In addition, the findings support the earlier studies that stocks with low liquidity and volume are more prone to manipulation. Lastly, the study finds that market manipulation has no significant impact on the illiquidity ratio, implying that the stock price sensitivity to trading volume remains largely unchanged after the manipulation.

The study proceeds as follows. Section 2 reviews the existing literature and outlines the theoretical framework used to measure market quality. Section 3 describes the data and market quality variables, then it presents the method. Section 4 presents the results and discusses the univariate analysis and regressions. Section 5 concludes our findings.

2. Literature review

The following section starts by introducing market manipulation. Then, it presents the existing literature about measurements that have been identified to facilitate a better understanding of market quality.

2.1. Introduction to market manipulation

The market strives to be a perfectly competitive and efficient, with the price of a stock reflecting all available information of the firm, both public and private (Fama, 1970). The market does, however, fall short on this ideal (Akerlof, 1970). Privileged parties might have better information, such as non-public information which the rest of the market is not aware of. As a result of this information asymmetry, manipulators might use this knowledge to fool rational information seeking investors into trading stocks at manipulated prices. Thus, exploiting on the perception that there are more informed traders than others in the market.

Stock market manipulation are classified into three types by Allen and Gale (1992): action based, information based, and trade based manipulation. Action based manipulations occurs when the actual or perceived value of the underlying asset is caused by an action. In information based manipulations, the manipulator is spreading misleading rumors or releasing false information. Trade based manipulations are considered more difficult to detect and occurs when a stock is manipulated by simply being bought and then sold, without using publicly observable actions or misleading information to change the stock price. The dataset for our study examines 31 cases of which 65% was classified as action based whilst the rest trade based (see table 5 in appendix). In this study, we will focus on the impact manipulation has on market quality measures, not taking into consideration of manipulation type. Therefore, an extended literature review of the different manipulation types is considered out of our scope.

Majority of studies of market manipulations are theoretical with quantitative model solutions, with only a few empirical studies. Several noteworthy studies have focused on modelling manipulation behavior and further studied the consequences of manipulation (eg. Vila, 1989; Allen & Gale, 1992; Allen & Gorton, 1992; Bagnoli & Lipman, 1996). In the recent years, researchers have begun to pay more attention to empirical studies of market manipulation (Aggarwal & Wu, 2006; Allen et al, 2006; Gerace et al, 2014: Huang & Cheng, 2015; Akinmade et al, 2020; Ergün et al, 2021). In contrast to Aggarwal and Wu (2006) who examined manipulation in the US, an advanced market, most recent studies have been conducted in emerging markets, such as Asia (Gerace et al, 2014, Huang & Cheng, 2015), Middle East (Ergün et al, 2021), and Africa (Akinmade et al, 2020). Typically, emerging markets are characterized by weak investor protection and subject to less rigid securities regulation (Huang & Cheng, 2015).

To our knowledge, only three other studies empirically analyse manipulation and its impact on market quality. Aggarwal & Wu (2006) studied cases from 1990 to 2001 and found that manipulators were mainly informed partied and their manipulation increased volatility, liquidity, and returns, causing prices to rise during the manipulation period and fall shortly after. Gerace et al (2014) studied manipulation cases from the Hong Kong stock exchange. Similarly, Akinmade et al (2020) studied the impact of stock market manipulation in Nigera. Gerace et al (2014) and Akinmade et al (2020) found manipulation to negatively impact market efficiency measures, such as bid-ask spread and volatility. Furthermore, both studies found that manipulation can occur in both low volume and high volume stocks, which challenges the claim of Easley and O'Hara (1987), that manipulation occurs in low volumes.

Based on an extensive literature search, we are to our knowledge the first to empirically investigate the impact manipulative stocks on the Nasdaq Stockholm Stock Exchange have on market efficiency by examining various market quality measures. In contrast to the emerging markets studied, Sweden is an intriguing market to examine because it has relatively stringent regulations and rules. It is therefore interesting to study if market quality can revert after a stock market manipulation, as opposed to less developed markets where it poses a risk to market efficiency (Gerace et al, 2014; Akinmade et al 2020). To account for the regulatory dimension, the cases selected for this study are after the EU legislations MiFID II and MiFIR went into effect. Section 3.1 provides an overview of the two pieces of legislation.

2.2. Literature and conceptual framework

Previous studies have primarily focused on market quality measures such as bid-ask spread, volatility, and volume when examining the impact of manipulation. In addition to the dimensions usually studied in relation to market manipulation, our study presents a different approach by also including illiquidity as a dependent variable in our regression analysis. Furthermore, by incorporating additional measures of market quality such as illiquidity and share turnover, which are considered as relevant market quality measures based on existing literature (Amihud, 2002; Subrahmanyam, 2005; Foran et al, 2015; Naik et al, 2020), our study provides a more comprehensive analysis of the impact of market manipulation on market quality.

The nature of market quality has been differently conceptualized in the literature. Finding an accurate measurement of market quality has thus been difficult for many researchers. In the next section, the theoretical framework is outlined by a short presentation of the most commonly applied market quality measures and how they have been applied in the literature.

2.2.1. Dependent variables to examine the impact of manipulation

2.2.1.1. Price

One of the most common measures of market liquidity and trading cost is the size of a security's bid-ask spread. The bid-ask spread is often referred to as the price of liquidity and reflects the market tightness; the cost of executing a transaction. It is extensively studied by researchers as a liquidity measurement (Amihud & Mendelson, 1986; Krinsky & Lee, 1996; Kyle, 1985). The spread, according to Aggarwal and Wu (2006), is a reliable metric for measuring information asymmetry and market efficiency. To better understand the spread, we employ market microstructure theory, which is regarded as a useful tool for analyzing market exchange, particularly in relation to information asymmetry (Bagehot, 1971).

The bid-ask spread is the key measure used in the market microstructure theory. The bid-ask spread is the difference in preferences buyers and sellers have regarding the price and volume for a stock. The markets are normally kept efficient through information-seeking investors. Thel (1994) describes that active information-seeking investors tries to identify "informed" traders to trade with. As discussed by Bagehot (1971), market participants always make a loss when they trade with an informed trader who possesses information that the other market participant does not have. Therefore, when market participants suspects that there might be informed traders present in a trade, they increase the spread of their transaction to compensate themselves. Therefore, the adverse selection risk associated with information asymmetry in the market is an important component of the spread.

This phenomenon was modelled by Allan and Gale (1992) where they could see that due to information asymmetry, investors were willing to trade with the informed trader at a lower value than the informed trader’s value, as they did not know if the informed trader actually was informed or a manipulator. However, by increasing the cost of trading, market participants are decreasing the market’s liquidity due to information asymmetry (Kyle, 1985). Similarly, the impact of information asymmetry in spreads was demonstrated by Krinsky and Lee (1996) who found that spreads widen before the release of information to the public and narrowed afterwards. Although the response of a widened spread is a rational response to the prospect of informed trading, the efficiency of the market is impacted negatively due to higher spreads.

The relationship between market manipulation and spread is persistent in recent empirical studies. Gerace et al (2014) found manipulation to negatively impact the bid-ask spread, suggesting that the spread reflected the concern of rational market participants trading with a manipulator which is in line with the market microstructure theory. This finding is aligned with the study conducted by Akinmade et al (2020) who found the bid-ask spread to widen in the post-manipulation period.

2.2.1.2. Volume

Depth in terms of trading volume is commonly used as a control variable and for benchmarking when measuring market quality. Previous research has suggested that large trades introduce an adverse selection risk (Easley & O'Hara, 1987). Albeit Easley and O'Hara (1987) discussed insider trading, the same bias is assumed to be true for manipulators. If manipulators have inflated the share prices to artificial levels, they would seek to trade in as large volume as possible to be able to capture the full profit before the prices returns to equilibrium. In fear of trading with a manipulator, market participants were found to increase their spread for larger trades (Easley & O'Hara, 1987). Therefore, volume is found to be a useful variable to determine level of information asymmetry as large trades are considered to contain an informational risk. Furthermore, this statement is in line with previous research which have concluded that there is an increased likelihood of successful manipulation in low liquidity/volume stocks (Thel, 1994; Aggarwal & Wu, 2006).

Recent empirical studies have found that manipulation has a significant negative impact on trading volume (Gerace et al, 2014; Akinmade et al, 2020). Furthermore, Gerace et al (2014) and Akinmade et al (2020) both concluded in their studies that manipulation can occur in both low volume and high volume stocks. Similarly, it has been discovered that manipulators require a large number of active traders in order to receive high returns (Aggarwal & Wu, 2006). These findings challenge the statement first proposed by Easley and O'Hara (1987), that manipulation primarily occurs at low volumes.

2.2.1.3. Illiquidity

Breadth is a price impact measure that refers to the market's ability to execute a trade, given certain volume, without significantly moving stock prices. According to Goyenko et al. (2009), the best price impact measure for measuring breadth is the Amihud Illiquidity Ratio as proposed by Amihud (2002). The measure is used to capture the tendency of illiquid assets being more sensitive to trades. Hence, a higher level of the Amihud measure corresponds with a lower level of liquidity (Amihud, 2002). Furthermore, Goyenko et al. (2009) compared various price impact measures and found the Amihud illiquidity ratio to be strongest correlated with microstructure-based price impact measures. Therefore, Amihud illiquidity ratio is found to be the best one to use to measure illiquidity in this study.

Studies show that most manipulations occur in relatively inefficient markets which are characterized by low liquidity and small market capitalization as these markets have an inelastic supply curve (Huang & Cheng, 2015). In many cases, they are lacking appropriate regulatory oversight or disclosure requirements. Aggarwal and Wu (2006) found that manipulators typically targeted 'penny stocks'; shares with low trading volumes and low market capitalization. As such, the largest stock exchange in the world the New York Stock Exchange (NYSE) only constituted of 2.11% of their manipulation sample and therefore being relatively free of manipulation. Similarly, Ergün et al (2021) observed that manipulators selected illiquid, underperforming, and less volatile stocks to manipulate. This supports the view of manipulators going for stocks with low liquidity and volume. The purchase of a manipulator in such market might have a larger price impact than in a more liquid market, thus making it easier to successfully execute manipulations (Thel, 1994).

To the best of our knowledge, illiquidity has not been tested in relation to manipulation. However, it is a common measure of market quality to examine the intensity of trading volume impact on prices (Chai et al, 2010; Naik et al, 2020). However, it should be noted, that the illiquidity ratio, like other liquidity measures, has some limitations. As pointed out be Grossman and Miller (1998), the ratio cannot distinguish whether the price fluctuations are a result of lack of liquidity or new information. To avoid unrelated events influencing the results, data from days of a company announcement was excluded from the data set.

2.2.2. Independent variables to examine the impact of manipulation

2.2.2.1. Share turnover

Share turnover is another popular metric used by researchers to measure market depth. The reciprocal of turnover is frequently used to represent the average holding period of securities (Atkins & Dyl, 1997), so a lower turnover rate corresponds to a longer average holding period. As a result, stocks with wider spreads have longer expected holding periods (Amihud & Mendelson, 1986). This means that turnover should be inversely related to spread but positively related to liquidity.

To the best of our knowledge, share turnover has not been tested in relation to manipulation. It is, however, a widely used indicator of market liquidity (Chai et al, 2010; Naik et al, 2020). In their study, Naik et al (2020) discovered that higher levels of turnover were associated with higher levels of liquidity. Although Chai et al. (2010) discovered similar patterns, they recognize that higher trading volume does not necessarily imply higher liquidity. Several studies have used turnover as a measure of liquidity (Stoll, 1978; Foster & Viswanathan, 1990), but others have questioned the use of turnover as a liquidity proxy and argued that turnover may be related to momentum (Subrahmanyam, 2005) or sentiment (Lee & Swaminathan, 2000). For example, Lee and Swaminathan (2000) discovered evidence in their study that turnover is not significantly correlated with firm size or bid-ask spread, but rather related to stocks' past performance.

2.2.2.2. Volatility

Manipulation is considered more likely to happen in volatile stocks (Aggarwal & Wu, 2006). Existing literature suggest that spread increases when volatility increases, similarly, it has been found that when stocks are riskier, their trading volume is lower (Aggarwal & Wu, 2006; Gerace et al, 2014; Naik et al 2020). As discussed by Gerace et al (2014), the increased volatility and reduced volume is associated with investors exiting the market as they are in fear of trading with a manipulator. Consequently, increased volatility has a negative impact on market liquidity and efficiency.

Moreover, Aggarwal and Wu (2006) and Gerace et al (2014) both found in their studies that volatility remained higher for manipulated stocks even after manipulation had occurred. Thus, indicating that manipulation continue to have an impact on the market in the post-manipulation period. On the contrary, Akinmade et al (2020) found volatility to be slightly lower in the post-manipulation period. The researchers explain this observation to be attributable to a policy measure proposed by the Nigerian Stock Exchange which placed a 10% limit on share price movements.

3. Data and methodology

The following section presents the data and methodology used to conduct the analysis. The study will examine Nasdaq Stockholm through a comprehensive sample of actual manipulation cases. Through an event study methodology, this study aims to examine the impact of manipulations on market quality.

3.1. Institutional Framework

Nasdaq Stockholm (formerly known as the Stockholm Stock exchange) is operated by Nasdaq Nordics and currently the largest stock exchange among Nasdaq's European stock exchanges (Nasdaq MarketInsite, n.d.). To support a company's growth journey through all stages, Nasdaq offer companies the possibility to list and raise capital on different markets based on their current stage: the Main Market, Nasdaq First North Growth Market and Nasdaq First North Premier Growth Market. As of 30 March 2023, Nasdaq Stockholm had 787 listed companies, of which 356 on the Main Market, 363 on First North Growth and 68 on First North Premier Growth (Shares - Share Prices for All Companies Listed on NASDAQ OMX Nordic - Nasdaq, n.d.-a). At the end of March 2023, the total market capitalization of the Main Market was SEK 9 789 billion, and SEK 263 billion on First North (Statistics - Nasdaq, n.d.). Nasdaq Stockholm is an order-driven market and stocks are traded between 9:00AM to 5:30PM.

3.1.1. Anti-manipulation regulation in Sweden

3.1.1.1. The Market Abuse Regulation

The Market Abuse Regulation (MAR) is an EU legislation that aims to prevent market abuse in financial markets. It replaced the earlier Market Abuse Directive (MAD) in 2016 and strengthened the regulatory framework for preventing market abuse. The legislation applies to all EU member states, as well as any companies whose financial products are traded on an EU-regulated market, and any individuals who trade such securities.

MAR prohibits trading based on insider information or to disclose insider information to others for the purpose of trading. Insider information is information that is not yet publicly available, but which, if made public, would significantly affect the price of a financial instrument. To hinder insider trading, MAR requires issuers to disclose insider information to authorities as soon as possible. MAR also prohibits manipulative practices for distorting the price of a financial instrument or for creating false or misleading signals about its supply, demand, or price. This includes disseminating false rumours, manipulating trading volumes, and participating in other deceptive market practices. In Sweden, the Swedish Financial Supervisory Authority (sw:

Finansinspektionen) is responsible for monitoring market compliance with the Market Abuse Regulation. They are also authorized to apply sanctions for such violations.

3.1.1.2. MiFID II and MiFIR

MiFID II (the Markets in Financial Instruments Directive) and MiFIR (the Markets in Financial Instruments Regulation) are two pieces of EU legislation that came into effect in January 2018. The aim is to improve financial market efficiency, transparency, and strength investor protection.

MiFID II requires financial firms to be more transparent about the products and services they provide, as well as to ensure that they are suitable for their clients. MiFID II also strengthened the rules governing conflicts of interest and introduced additional product governance requirements. It added new requirements for trading venues, such as rules for trading access and requirements for market making and other liquidity-providing activities. MiFIR is a supplement to MiFID II that specifies the reporting requirements for trading venues and financial firms. It requires real-time reporting of financial instrument transactions to relevant authorities, mandates the use of regulated trading venues, and sets guidelines for financial institutions providing investment services.

3.2. The data

This thesis uses a comprehensive dataset of market manipulation cases that were prosecuted by market regulators. These 183 cases of manipulation occurred between 2018 to 2023[1]. Information about the cases was collected from the Swedish Financial Supervisory Authority's webpage and in cooperation with Nasdaq Nordic's Trading Surveillance Team. The dataset only includes manipulation cases that occurred after MiFID II and MiFIR went into effect in January 2018, as these are considered as the most recent significant regulatory changes in the EU's anti-manipulation laws.

Since the purpose of this study is solely examine manipulation cases that are not a result of changes in the company's fundamentals, we did not include any cases related to insider trading to the dataset. By further excluding cases of manipulation of financial products other than stocks, and cases which occurred in other Swedish stock exchanges, the list was narrowed down to 54 cases. Similar to Gerace et al (2014), we use a time period of 200 days to examine the effects of the manipulation. Akinmade et al (2020) used a time period of 300 days which makes it possible to study a longer time frame. However, both studies found similar results which implies that using a time period of 200 days or 300 days do not yield different results. The smaller time period was chosen to be able to include as many cases as possible. Then, stocks that did not have any data

[1] Until 26 March 2023

100 days prior and 100 days after to the manipulation dates were excluded to ensure comparability of the cases. If the stock had been manipulated more than once during 2018-2023, the most recent manipulation case was chosen. The cases that met all the criteria as described above were considered within the scope and thus included in the dataset. A net list of 31 manipulated stocks and their respective manipulation periods was thus obtained (see table 4 in the appendix).

Graph 1 shows that the majority of the manipulated stocks analyzed are listed in First North Stockholm. Table 1 presents the mean and median values of various metrics for the 200-day event period of the manipulated stocks and for years 2018-2022 for the Main Market and the First North Stockholm listed stocks. For descriptive characteristics of manipulation cases, see table 5 in the appendix.

The market cap and trading volume of First North Stockholm is significantly lower than for the Main Market. Furthermore, the market cap and trading volume for the manipulated stocks are considerably lower than the average of First North Stockholm, suggesting that our sample is characterized by small stocks with low trading volumes. The characteristics of our manipulated sample is thus aligned with existing literature which suggest that manipulated stocks are typically stocks with low trading volume and low market capitalization (Aggarwal & Wu, 2006; Huang & Cheng, 2015).

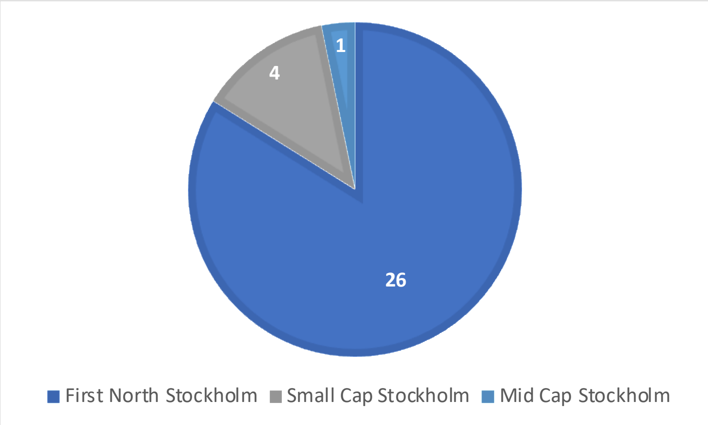
Table 1. Characteristics of manipulated stock portfolio and stock indexes

The table below presents market cap, average price, turnover and trading volume of the 31 manipulated stocks used in this thesis, Nasdaq Stockholm Main Market for the years 2018-2022, and Nasdaq First North for the years 2018-2022.

	Market Cap	Average Price (SEK)	Turnover	Trading Volume
Summary statistics of manipulated stocks during the study period.				
Mean	503 563 267	17.10	1 408 838	144 931
Median	196 253 404	5.67	170 346	34 678
Summary statistics of Nasdaq Stockholm Main Market for the years 2018–2022.				
Mean	19 730 220 420	170.92	43 464 069	860 759
Median	2 171 593 744	69.89	2 607 376	72 364
Summary statistics of Nasdaq First North Stockholm for the years 2018–2022.				
Mean	702 601 545	32.56	1 423 989	367 741
Median	126 513 127	8.64	204 053	31 642

Graph 1. The stock listings of manipulated stocks

The pie chart below illustrates the distribution of the 31 manipulated stocks across various stock lists.



3.2.1. Preparation of data

The study uses the tool 'event study' to empirically test how the market responds to manipulation. Event studies are a robust econometric tool which were originally used to test the relationship between market prices and the earnings of a company (Ball & brown, 1968). Event studies have since then also been widely used by the US courts to study the effect of market manipulations (Schwert, 1981; Leas, 1974). When determining whether false information is causing a security to trade at an 'artificially high or low' price, the methodology of an event study is considered robust (Fischel, 1982).

This study utilizes the market microstructure analysis method by using the bid-ask spread, volume and illiquidity as indicators of market quality. Therefore, we collected trading volumes, end-of-day bid and ask quotes, as well as intra-day closing, high and low prices from the Nasdaq Nordic's database for all manipulated stocks. Pre- and post-manipulation periods of 100 days each were used to study the effects of manipulation on the stock market.

At first, the dataset of daily trading activity was summarized into daily measures as described later in 3.2.2. The date or dates of the manipulation was designated as the 'event' date. In cases where manipulation has been detected for several days or months, the event date is defined to be the average of the daily data points between the start and end of the manipulation period. Data from days of a company announcement was excluded from the data set to avoid unrelated events influencing the outcome. To examine the impact of the manipulations and its ability to move market prices returns and other explanatory variables were used.

After an examination of the daily measures, it was discovered that the illiquidity variable had a high skewness in its distribution. Outliers were primarily caused by extremely low trading volumes in a few stocks on a few days. Because these outliers were simply irregular in comparison to the other data points and did not represent impossible or erroneous outcomes, a log transformation was used to de-emphasizes the impact of extreme values. The graph 9 in the appendix shows the raw and the log-transformed data points.

3.2.2. Definition of variables

3.2.2.1 Variables to examine market price movements

Return: To examine the ability of the event to move market prices, returns are used. The measure reflects the daily return of a stock.

$$Return_{\ i,t} = \frac{S_{i,t} - S_{i,t-1}}{S_{i,t-1}} \tag{3.1}$$

where $S_{i,t}$ is the closing share price of stock *i* on day *t*.

3.2.2.2 Dependent variables to examine the impact of manipulation

PBAS: The Bid-Ask Spread have been used to evaluate the tightness in the market which is the amount of cost acquired by an investor for transacting a security. The bid-ask spread has been recognized as an important measure of liquidity, information asymmetry and efficiency. However, compared to the Bid-Ask Spread which reflects the raw spread, the Proportional Bid-Ask Spread, hereafter referred to as PBAS, bid-ask spread or simply spread, is further elevated as it shows the *relative* quoted spread which is standardized by the quote midpoint. It is considered a better variable to measure variations in stock prices over time and across stocks (Yilmaz et al, 2015).

To test the price dimension (spread) in manipulated stocks, PBAS will be a dependent variable used in the first regression but act as an explanatory variable in the second regression. As higher levels of the spread are associated with lower levels of liquidity, the expectation is that the PBAS will increase after manipulation.

$$PBAS_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{(Ask_{i,t} + Bid_{i,t})/2} \tag{3.2}$$

where $Ask_{i,t}$ is the close of trade ask price of stock *i* on day *t* and $Bid_{i,t}$ is the close of the trade bid price of stock *i* on day *t*. The denominator is the mean (midpoint) of $Ask_{i,t}$ and $Bid_{i,t}$.

Volume: The total number of shares traded on a specific day for a stock is the trading volume of the day for that specific stock and measures stock's liquidity. Trading volume is also found to be a useful variable to determine level of information asymmetry. For all manipulated stocks, daily trading volumes have been collected. To bring the values on to a comparable scale, the daily volume data used in regression analysis is transformed into log form.

To test the quantity dimension (volume) in manipulated stocks, volume will be a dependent variable used in the second regression but act as an explanatory variable in the first regression. Researches have suggested that trade size could advocate for adverse selection, suggesting that investors would raise spreads for larger trades. Considering the markets concern of information asymmetry, volume is expected to decrease after manipulation.

$$Volume_{i,t} = log\left(Vol_{i,t}\right) \tag{3.3}$$

where $Vol_{i,t}$ is the number of shares traded for stock *i* on day *t*.

Illiquidity: To evaluate manipulation's impact to the stock market breadth, the illiquidity dimension is tested. Market breadth refers to the ability of the market to smoothly enable trading of a specific quantity without influencing the share price too much. Amihud illiquidity measure is considered the best measure for price impact according to Goyenko et al (2009). The measure is calculated as the absolute value of daily return divided by the trading volume. As a result of skewness in its distribution, we take the logarithm of this measure similar as Foran et al (2015).

To test the illiquidity dimension in manipulated stocks, illiquidity will be a dependent variable used in the third regression but act as an explanatory variable in the first two regression. Stocks with a high Amihud measure who generates higher returns tends to be more illiquid, which indicates a narrow market breadth. The expectation is therefore that the ratio will be high as existing literature has concluded that manipulated stocks tends to be highly illiquid.

$$Illiquidity_{i,t} = log\left(\frac{\left|Return_{\ i,t}\right|}{Vol_{i,t}^{SEK}}\right) \tag{3.4}$$

where $Vol_{i,t}^{SEK}$ is the trading volume in SEK (currency) for stock *i* on day *t*.

3.2.2.3 Explanatory variables to examine the impact of manipulation

Volatility / Risk: To measure the risk or volatility of a stock, a simple measure of volatility is defined as the logarithmic difference between the intraday high and low prices. Based on previous research, the expectation is that volatility will increase after manipulation as it will be similar to the Bid-Ask spread, build upon the markets concern of information asymmetry.

$$Volatility_{i,t} = log\left(H_{i,t}\right) - log(L_{i,t}) \tag{3.5}$$

where $H_{i,t}$ is the high of the day of stock *i* and $L_{i,t}$ the low of the day of stock *i* on day *t*.

Share turnover: Share turnover is used to investigate the depth of liquidity which refers to the extent to which large amount of orders is available in the market to maintain equilibrium in the stock's market price. For a deep market to exist it is dependent of the number of stocks traded in the market. Share turnover is considered a suitable measure of depth as it considers volume traded in proportion to the number of shares outstanding, measuring the frequency of shares being traded. Due to varying results of share turnover from previous research, the expected impact of share turnover is therefore uncertain.

$$Share\ turnover_{i,t} = \frac{Vol_{\ i,t}}{SO_{i,t}} \tag{3.6}$$

where $SO_{i,t}$ is the number of shares outstanding for stock *i* on day *t*.

3.2.2.4 Other variables

Dichotomous Variable: Before the event date, the binary variable or dichotomous variable takes on the value of 0 and after the event date, it takes on the value of 1.

$$D_{i,t} = \begin{cases} 0, if\ observation\ falls\ before\ event\ date \\ 1, otherwise \end{cases} \tag{3.7}$$

Relative Date: To study the effects of the manipulation on the market a time period around the event needs to be identified. The following study uses a time period of 200 days. The cases have as such, been examined over the 100 prior days before the manipulation and 100 days after. Cross-sectional averages have been calculated for each relative day to be able to compare the manipulation across cases. The cross-sectional averages of the explanatory variables have been used to measure the interest of the market, that is, the buying and selling. To make sure that the data is comparable and avoid "infection" by unrelated events, data from days of a company announcement have been removed.

$$\tau = -100, 100 \tag{3.8}$$

Table 2. Cross-Sectional Averages

The time series for each variable are computed for 100 days before and after the manipulation date. The table below presents three different sample periods: the first four days, five days around the manipulation date, and the last four days.

Relative Date	PBAS	Return	Illiquidity	Volatility	Share Turnover	Vol
-100	0.0047	0.0040	0.0000003	0.0562	0.0044	176 905
-99	0.0054	-0.0018	0.0000002	0.0563	0.0023	133 333
-98	0.0043	-0.0023	0.0000002	0.0553	0.0028	138 716
-97	0.0045	-0.0001	0.0000007	0.0614	0.0023	151 520
-2	0.0067	0.0232	0.0000045	0.1020	0.0044	166 902
-1	0.0066	0.0054	0.0000035	0.0973	0.0049	258 874
0	**0.0126**	**0.0431**	**0.0000123**	**0.1564**	**0.0049**	**287 630**
1	0.0070	-0.0151	0.0000007	0.0987	0.0025	127 800
2	0.0059	-0.0075	0.0000007	0.0733	0.0023	126 243
97	0.0073	-0.0191	0.0000017	0.0703	0.0030	244 400
98	0.0081	0.0093	0.0000012	0.0839	0.0022	133 288
99	0.0070	0.0007	0.0000008	0.0657	0.0024	157 759
100	0.0057	-0.0007	0.0000010	0.0690	0.0021	136 352

To study the effects of the manipulation on the market, time series of cross-sections are calculated for the following variables for 100 days before the manipulation and 100 days after the manipulation: the proportional bid-ask spread, returns, illiquidity, volatility, share turnover and volume.

3.3. Regression Model

To robustly assess the market reaction to manipulation we blend univariate testing with regression analysis. The use of univariate analysis is essential for evaluating the impact of manipulation on the spread, return, illiquidity, turnover, volatility, and volume. For the analysis, the means between the pre-event and post-event periods will be compared.

Furthermore, based on the three dimensions identified in our theoretical framework, we use three sets of regression analysis to test the results. The first to test the price dimension (spread), the second to test the quantity dimension (volume) and the third to test the illiquidity dimension. The returns are, however, not used in the regressions as an explanatory variable as risk and return are highly correlated variables. Including returns would therefore give us results with multicollinearity.

3.3.1. Set 1 – Price analysis

Our first regression set is used to test the liquidity price dimension. The following regression equations will thus be used to test how statistically significant each one of the explanatory variables are to our dependent variable PBAS.

Regression set 1

$$PBAS = \alpha + \beta_1 D_{i,t} + \varepsilon_{i,t} \tag{3.9}$$

$$PBAS = \alpha + \beta_1 D_{i,t} + \beta_2 Volume_{i,t} + \beta_3 Volatility_{i,t} + \beta_4 Share\ turnover_{i,t} + \beta_5 Illiquidity_{i,t} + \varepsilon_{i,t} \tag{3.10}$$

Each independent variables corresponding coefficient is given by β, α the intercept term and ε_t the error term.

For the first equation (3.9) we regress PBAS to the dummy variable. To identify to which extent manipulation affects the spread, the dichotomous variable is used as the only explanatory variable in those equations. In the latter equation (3.10) volume, volatility, share turnover, and illiquidity measures are introduced.

3.3.2. Set 2 – Quantity analysis

Our second regression set is used to test the quantity dimension. The stock's trading volume is thus set as the dependent variable whilst the dummy, PBAS, volatility, share turnover and illiquidity are explanatory variables.

Regression set 2

$$Volume = \alpha + \beta_1 D_{i,t} + \varepsilon_{i,t} \tag{3.11}$$

$$Volume = \alpha + \beta_1 D_{i,t} + \beta_2 PBAS + \beta_2 Volatility_{i,t} + \beta_4 Share\ turnover_{i,t} + \beta_5 Illiquidity_{i,t} + \varepsilon_{i,t} \tag{3.12}$$

Each independent variables corresponding coefficient is given by β, α the intercept term and ε_t the error term. In the first equation (3.11), the dichotomous variable is used as the only explanatory variable to identify to which extent manipulation affects the volume. In the latter equation (3.12), PBAS, volatility, share turnover, and illiquidity measures are introduced.

3.3.3. Set 3 – Illiquidity analysis

Our third regression set is used to test the illiquidity dimension. The Amihud Ratio is used as the dependent variable in the following equations, with the dummy, PBAS, volume, volatility, and share turnover acting as explanatory variables.

Regression set 3

$$Illiquidity = \alpha + \beta_1 D_{i,t} + \varepsilon_{i,t} \tag{3.13}$$

$$Illiquidity = \alpha + \beta_1 D_{i,t} + \beta_2 PBAS + \beta_3 Volume + \beta_4 Volatility_{i,t} + \beta_5 Share\ turnover_{i,t} + \varepsilon_{i,t} \tag{3.14}$$

Each independent variables corresponding coefficient is given by β, α the intercept term and ε_t the error term. In the first equation (3.13), the dichotomous variable is used as the single explanatory variable to determine the extent to which manipulation affects illiquidity. In the latter equation (3.14), other variables are introduced to determine the degree to which the PBAS, volume, volatility and share turnover relates to the illiquidity.

4. Results and Discussion

The following section presents the univariate results and the outcome of the regression analysis. The empirical findings of the data are then analyzed and discussed based on existing literature.

4.1. Univariate Results

Firstly, we investigate each variable individually to describe patterns found in the data, using measures of central tendency and graphical methods. To accurately understand how much the market measures are impacted by manipulation, it is important to compare the descriptive statistics of the pre-event and post-event period. The regression analysis is then performed in section 4.2 to further investigate the relationships between the variables.

The univariate findings suggest that the spreads, returns, liquidity, volatility, and trading volume are all affected by market manipulation (see graphs 2 to 7 below). We compare the variable averages to the pre- and post-manipulation means as well as the manipulation date mean. Graphs below shows that the metrics on the day of manipulation are distinct from the pre, post, and total averages. The manipulation period is associated with a wider spread, as well as with higher volatility. The means spike at event date for both volatility and PBAS, as shown in graphs 6 and 1. These findings imply that manipulation affects stock's spread and increases its volatility. Consequently, we see that PBAS and volatility remains higher in the post-manipulation period than pre-manipulation period.

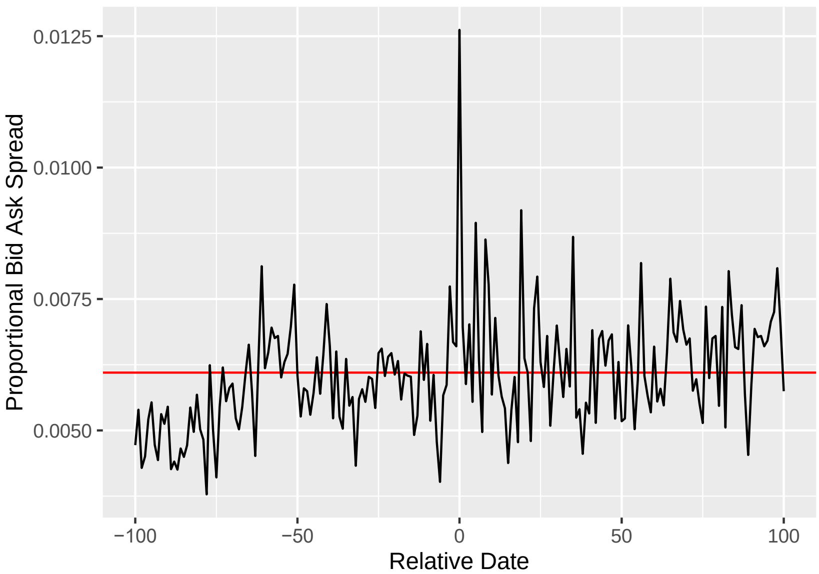
Returns, and so prices, increased on the day of the manipulation (see graph 3). Event day return mean is 1 758% greater than the pre-event mean, 4 018% than the post-event mean, and 2 794% greater than the total mean. This demonstrates that the manipulators were able to artificially inflate prices and most likely profit from the manipulation.

The illiquidity ratio shown in graph 4 suggests that there is a decrease in stock illiquidity during the manipulation date. This result indicate that stock liquidity is affected by and briefly increased by market manipulation. This is consistent with the findings of other volume-based metrics. The average share turnover during the manipulation period is higher compared to other averages, implying that more stocks were traded during the manipulation period. Consequently, we see that manipulated stocks remains highly illiquid in the post-manipulation period than pre-manipulation period.

Additionally, graphs 6 and 7 show that the trading volume on the manipulation date is greater than pre-manipulation. On the date of a manipulation, the manipulators may engage in increased trading activity to carry out their manipulative scheme. 9 out of 31 cases studied in this thesis were so called “wash trading” cases. Wash trading is a type of market manipulation in which trading volumes of a particular security are artificially increased, typically by trading with oneself, with the intention of sending out false market signals that the security is more desirable. Other traders in the market may respond to the manipulative activity by increasing their own trading activity. This could involve attempting to take advantage of the price movements created by the manipulators or trying to protect themselves from potential losses. Graph 7 demonstrate how trade volume increases during the manipulation and stays higher after day 0. The increasing trend in trading volume could be linked to the growing interest in trading and stock markets, as supported by the annual share trading figures from Nasdaq Nordics (Statistics - Nasdaq, n.d.). These figures demonstrate that the overall number of transactions has been on the rise since the turn of the century, particularly in recent years. Regression analysis is conducted to further understand this trend in the next section.

Graph 2. Proportional Bid-Ask Spread

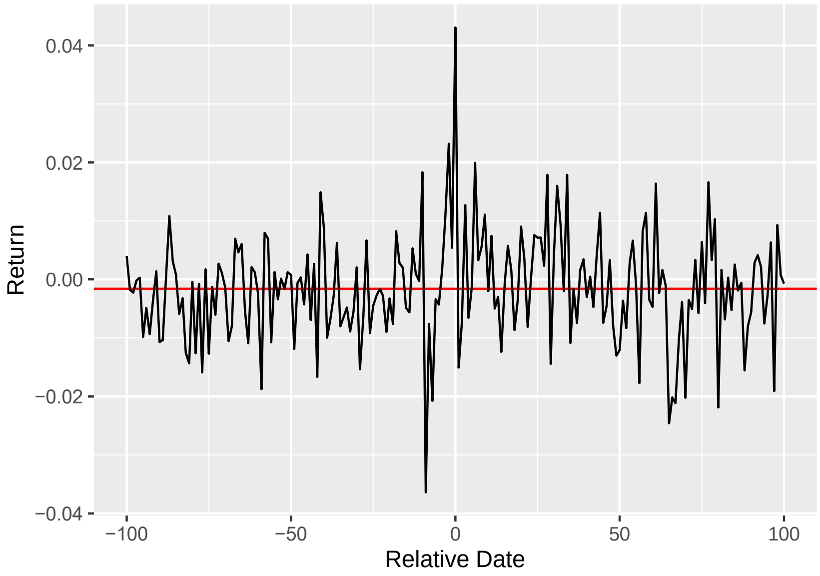
The following graph illustrates the average proportional bid-ask spread for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	PBAS
Pre-manipulation	0.0057
Post-manipulation	0.0063
Event Mean	0.0126

Graph 3. Return

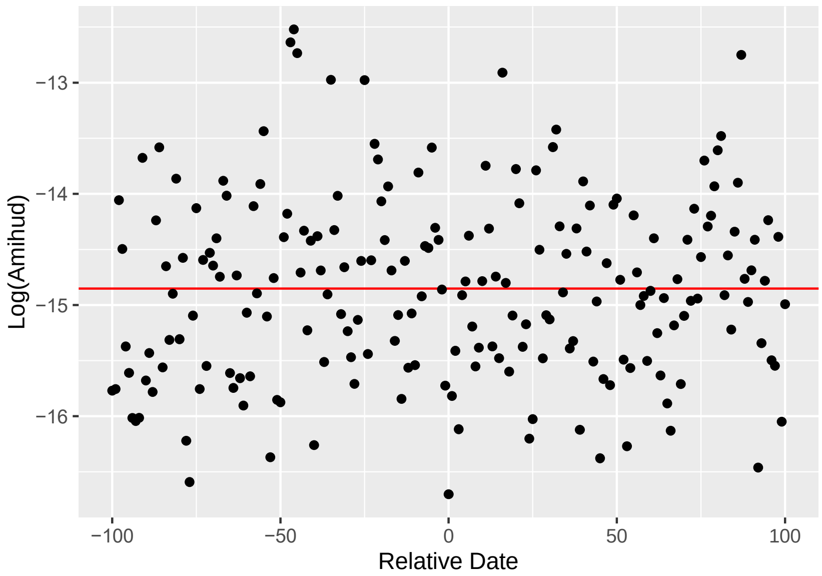
The following graph illustrates the average returns for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Return
Pre-manipulation	-0.0026
Post-manipulation	-0.0011
Event Mean	0.0431

Graph 4. Illiquidity

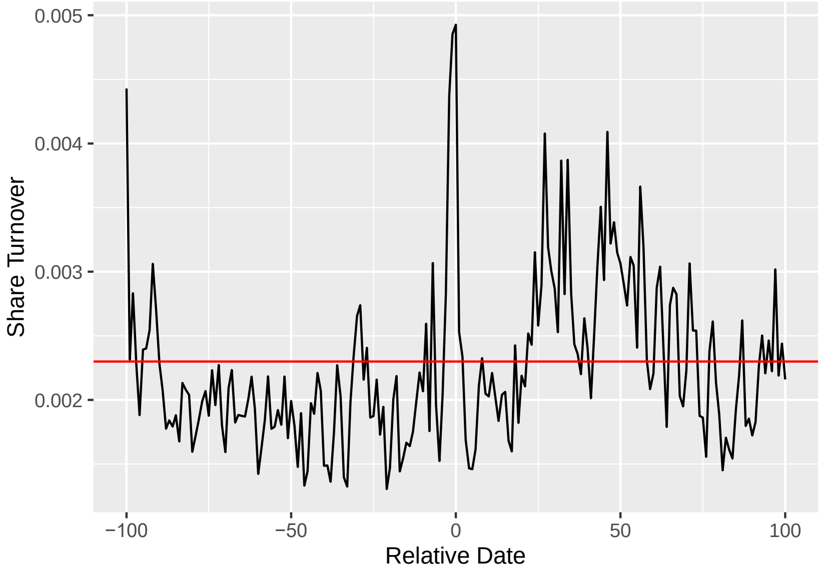
The following graph illustrates the illiquidity (Amihud ratio) in log form for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Illiquidity
Pre-manipulation	-14.8161
Post-manipulation	-14.6873
Event Mean	-16.7018

Graph 5. Share Turnover

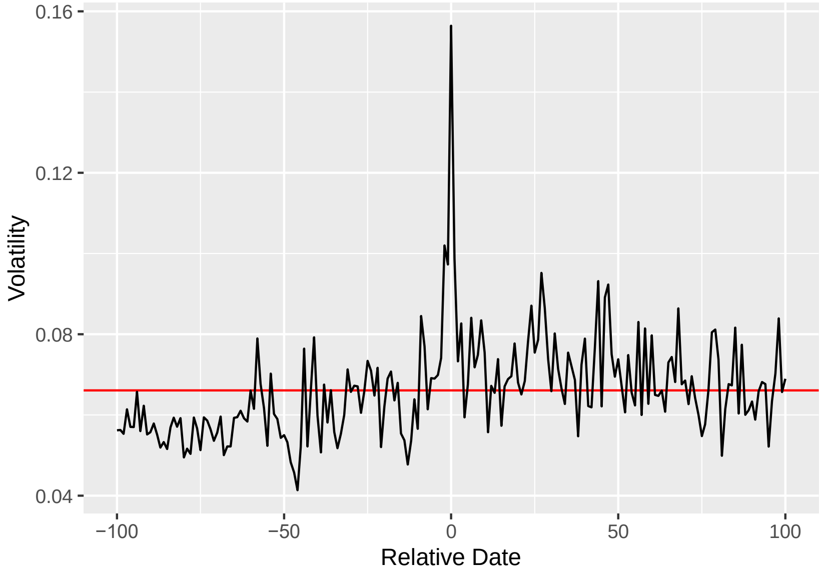
The following graph illustrates the average share turnover for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Share Turnover
Pre-manipulation	0.0020
Post-manipulation	0.0024
Event Mean	0.0049

Graph 6. Volatility

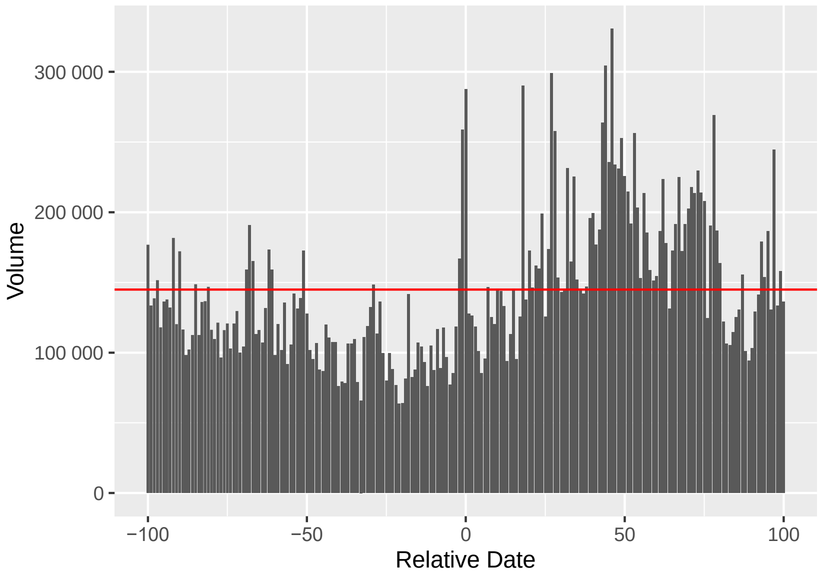
The following graph illustrates the average volatility for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Volatility
Pre-manipulation	0.0608
Post-manipulation	0.0705
Event Mean	0.1564

Graph 7. Volume (total)

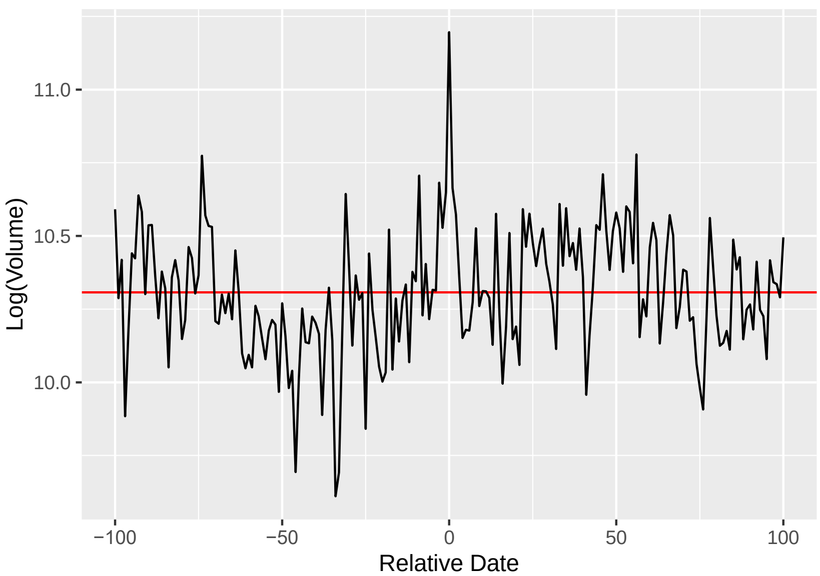
The following graph illustrates the volume traded (Vol) for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Vol
Pre-manipulation	116 731
Post-manipulation	171 703
Event Mean	287 630

Graph 8. Volume (Log)

The following graph illustrates the volume traded in log form for the 31 manipulated stocks. The red line represents the total mean of the 200 period. Day 0 is the manipulation date. The descriptive averages for the 31 manipulated stocks are shown in the table to the right.



	Volume
Pre-manipulation	10.2600
Post-manipulation	10.3457
Event Mean	11.1957

4.2. Regression model

In this section, we present the results of the regression analysis along with their statistical interpretation. Table 3 shows the coefficients and standard errors of the estimates for equations 3.9 to 3.14. Set 1 examines the price dimension (spread), set 2 the quantity dimension (volume), and set 3 analyses the illiquidity dimension (Amihud Ratio). To control for multicollinearity among the independent variables, we used Variance Inflation Factors (VIF). The results can be found in table 6 in the appendix.

Table 3. Regression Results for a 200-day event period

This table summarizes the regression analysis results for the manipulation cases (equations 3.9 to 3.14). The coefficients for the explanatory variables are presented, and the standard errors of the estimates are shown in parenthesis. ***,**, * denotes statistical significance at 0.1%, 1% and 5% levels respectively.

	Intercept	Dummy	PBAS	Volume	Volatility	Share Turnover	Illiquidity
Set 1 – Price analysis							
PBAS (Dependent)							
Equation 3.9	0.006***	0.001***					
	(0.000)	(0.000)					
Equation 3.10	0.012**	0.0005**		-0.001*	0.042***	-0.179	0.000
	(0.004)	(0.000)		(0.000)	(0.007)	(0.134)	(0.000)
Set 2 – Quantity analysis							
Volume (Dependent)							
Equation 3.11	10.260***	0.086**					
	(0.020)	(0.028)					
Equation 3.12	8.955***	0.001	-28.317*		4.283**	150.408***	-0.061***
	(0.208)	(0.025)	(12.444)		(1.326)	(21.080)	(0.013)
Set 3 – Illiquidity analysis							
Illiquidity (Dependent)							
Equation 3.13	-14.816	-0.051					
	(0.082)	(0.116)					
Equation 3.14	1.288	0.070	-65.156	-1.567***	6.083	-10.436	
	(3.435)	(0.126)	(63.958)	(0.347)	(6.910)	(120.456)	

4.2.1. Statistical interpretation – Price analysis

The first regression in the first set examines the relationship between the bid-ask spread and the dummy variable that represents the dataset change post-manipulation. Focusing solely on the dummy variable allows us to determine the effect of manipulation on the spread. The positive coefficient (0.001) with a statistically significant result at the 0.1% level suggests with strong evidence that the spread increased after the manipulation period. This is an insightful finding, especially when isolating the impact of manipulation on the spread solely.

The dummy variable is also found to be significant at the 1% level in the second regression, providing statistical evidence that the post-manipulation period is related to an increase in spreads. The result implies that the bid-ask spread increased during the manipulation period and then remained wide. A wider spread is indicative of a less tight market, which in turn implies low liquidity and high transaction costs. Since high liquidity is one of the essentials for a well-functioning stock market, market manipulation appears to distort market quality in terms of market tightness. Fewer traders may be actively trading the security as wider spread raises the cost of trading. Gerace et al (2014) confirm the findings, implying that an increased spread reflects rational market participants' concern when trading with a manipulator. They may choose to exit the market, making the market less effective and making it more difficult to trade at a fair price. As a result of the first regression set, market manipulation appears to have a significant impact on the bid-ask spread.

The positive coefficient of volatility in the second regression (0.042) suggests that, all else being equal, a 1% increase in volatility leads to a 4.2% increase in the spread. This finding is significant at the 0.1% level and supports the literature on the inverse relationship between the spread and market efficiency (Kyle, 1985). Manipulation increases volatility, which in turn widens the spread by 4.2%, indicating that market efficiency is harmed by manipulation. Wider bid-ask spread associated with manipulation supports the literature-suggested models in which market participants incorporate an informational risk into spreads. Thus, we can see that market manipulation appears to reduce liquidity and market efficiency as suggested by Krinsky and Lee (1996). Market participants are aware of this risk and factor it into their trading decisions. As a result, both spread and volatility tend to increase following manipulation, reflecting the concerns of market participants about trading with a manipulator. These results align with Kyle's (1985) argument that information asymmetry among market participants leads to an increase in trading costs and in result harms the market liquidity.

Albeit the volume coefficient is a small negative figure (-0.001), the result confirms the negative relationship between bid-ask spread and trading volume. Volume is significant at the 5% level. This inverse relationship is likely due to information asymmetry, where rational market participants are concerned about trading with a manipulator (Gerace et al, 2014). Moreover, the findings of Thel (1994) and Aggarwal and Wu (2006) show that successful manipulation often happens in stocks with low volume and liquidity. This is consistent with the negative relationship between spread and volume, indicating that the analyzed stocks in this study are illiquid and have low trading volume. As shown in Table 2, these stocks had a significantly lower trading volume compared to the Main Market and even lower average trading volume than Nasdaq First North.

The coefficient for share turnover suggests a negative relationship between the variables. As proposed by the literature, high turnover is associated with high liquidity. Considering the negative relationship with the spread, the coefficient in share turnover further confirms that manipulation occurs in stocks with low liquidity (Thel, 1994; Aggarwal & Wu, 2006). However, the statistical analysis shows that this result is insignificant at any significance level, making it infeasible to determine with certainty the relationship between these variables. As pointed out by Subrahmanyam (2005), and Lee and Swaminathan (2000), share turnover can also be related to either momentum or sentiment rather than liquidity.

Hasbrouck (2009) finds that Amihud illiquidity ratio is highly correlated with various other illiquidity measures such as the bid-ask spread. The coefficient for illiquidity is positive but very small (0.000), the result is neither found to be statistically significant. This suggests that we cannot determine with certainty the relationship between the sensitivity of the stock prices to order flows (market breadth) and the level of costs incurred by investors in trading securities (market tightness).

Except for the share turnover and illiquidity, the first regression set generates statistically significant results. Low standard errors also suggest that the coefficient estimates are fairly accurate. These results are consistent with earlier research indicating that market manipulation is increasing bid-ask spreads (Akinmade et al, 2020; Gerace et al, 2014). Since the spread is a commonly used measuring market quality metrics such as cost of trading, market efficiency and information asymmetry, the first regression set suggests that market manipulation is influencing market quality and the efficiency of the market.

4.2.2. Statistical interpretation – Quantity analysis

The second set of regressions is using volume as a dependent variable. The first regression in the second set, which is regressing the volume onto the dummy variable, shows a p-value of 0.003 making variable significant at the 1% level. This indicates that market manipulation is statistically significant with respect to trading volume.

The second regression model regresses volume on the dummy variable, bid-ask spread, volatility, share turnover, and illiquidity. This regression, however, shows no significant relationship between volume and the dummy variable. This implies that the dummy variable is not a significant predictor of trading volume after the effects of other variables are taken into account. To put it differently, the first regression suggests that trading volume is slightly higher on average post-manipulation but, upon controlling for other variables, it was discovered that market manipulation may not be the cause of this increase. Worth noting, with an increased number of variables in the regression model, the power of statistical test may decrease; with these additional variables, the small sample size of this study may not be sufficient to identify the true influence of the dummy variable.

Albeit the second regression do not find a statistically significant result between volume and the dummy variable, it finds a statistically significant results with volume and all other explanatory variables. The regression analysis discovers an inverse relationship between PBAS and volume, such as in the first regression set. PBAS is significant at the 5% level. Nevertheless, the result is consistent with earlier studies which suggest that manipulated stocks tend to have low liquidity due to low trading volume (Thel, 1994; Aggarwal & Wu, 2006). Additionally, rational investors have concerns which increase the inherent informational risk in the spreads (Gerace et al, 2014). Similarly, illiquidity is inversely related to trading volume. Amihud ratio is significant at the 0.1% level. The second regression shows that higher volume narrows the bid-ask spread and reduces stock illiquidity. The results are thus confirmed by earlier research, suggesting that manipulation rarely occurs in high volume stocks (Thel, 1994; Aggarwal & Wu, 2006), which are also characterized by wide spreads and low liquidity.

The relationship between volume and both PBAS and illiquidity suggests that when the spread is wide and the stock is illiquid, market participants avoid trading. On the contrary, the second regression reveals a positive relationship between trading volume and volatility, indicating that as stocks become riskier, market participants continue to trade, leading to an increase in trading volume. Volatility is significant at the 1% level. This finding contradicts previous studies by Aggarwal and Wu (2006), Gerace et al. (2014), and Naik et al. (2020), which suggest that low trading volume leads to an increase in volatility. However, the results can be explained by the theory proposed by Easily and O'Hara (1987) that manipulators prefer trading in larger volumes. Given that volatile stocks are more likely to be manipulated, market participants might expect to earn higher profits by trading in larger volumes when the stock is volatile. Furthermore, market manipulation schemes may increase volatility as information-seeking traders react to changes in stock price caused by manipulators, resulting in increased trade volume.

Increasing share turnover is additionally connected to higher trading volume. Share turnover is statistically significant at the 0.1% level. The highly significant relationship is not surprising given that both variables assess market activity and represent the extent of stock participation. Hence, increasing trade volume is positively associated to a deep market, as it helps to maintain market price equilibrium and reflects greater liquidity. A deeper market with higher liquidity offers better possibilities to buy and sell shares without major price effect. These findings are consistent with earlier research indicating manipulation happens seldom in large volume stocks (Thel, 1994; Aggarwal & Wu, 2006), i.e. stocks with high liquidity and good depth. Thus, the result of the second regression imply that manipulation may be more difficult to accomplish in a deep stock market.

The results of the second regression set show significant relationships between trading volume and the explanatory variables, except for the dummy variable. Hence, there is no conclusive evidence to prove that market manipulation affects trading volume. Both Akinmade et al (2020) and Gerace et al (2014) found similar results in their studies when analyzing the impact of manipulation on trading volume, suggesting that manipulation is possible when volume is high, and not only when it is low. This finding is therefore raising a renewed concern and it challenges the suggestion that manipulation occurs primarily in low volumes (Easily and O'Hara, 1987).

4.2.3. Statistical interpretation – Illiquidity analysis

In the third set of regressions, the relationship between market breadth and other market quality measures are examined by using illiquidity ratio as the dependent variable. The first regression in the third set examines the relationship between illiquidity and the dummy variable that represents the dataset change post-manipulation. The negative coefficient with no statistically significant result shows that it cannot be determine with certainty whether the illiquidity dimension is impacted by market manipulation.

The second regression also generates insignificant results. The second regression indicates that there is no statistically significant relationship between illiquidity and the independent variables, except for trading volume. There does not appear to be a significant relationship between illiquidity and spread, stock volatility, or share turnover. As in the second set of regressions, the regression analysis still shows an inverse relationship between illiquidity and trading volume. This finding is highly significant at the 0.1% significance level and supports previous research suggesting that manipulated stocks tend to have low liquidity due to low trading volume (Thel, 1994; Aggarwal & Wu, 2006).

In section 4.1, we observed a short-term decrease in stock illiquidity as a result of manipulation, but the regression analysis showed that manipulation does not have a significant impact on illiquidity. As the illiquidity variable was chosen to be the measurement of the stock market's breadth, our findings suggest that the breadth component of market quality is likely not to be influenced by market manipulation. This is an interesting finding as we earlier found that the liquidity price dimension has been adversely affected by manipulation, and therefore, we can conclude that different market quality measures respond differently to market manipulation.

5. Conclusion

This study empirically investigates the impact of stock market manipulation on market efficiency by examining the reactions of market quality measures on the Stockholm stock exchange. The objective has been to examine whether manipulation distorts the stock market, both during the manipulation but also after the manipulation period. To empirically test the market response to manipulation, this paper is analyzing market quality measures based on daily stock data using an event study methodology, univariate analysis, and regression analysis.

The study finds that the impact of market manipulation to market quality is negative. According to the univariate analysis, market manipulation had an impact on all quality measures at the day of manipulation, and several of them continued even after the manipulation period was over. Similarly, the regression analysis is confirming that manipulation on the Stockholm stock exchange exposed a significant level of inefficiency, making it challenging to maintain fair pricing. However, our regression results find that manipulation has no apparent impact on all the three market quality dimensions tested in this study. First, the study finds that the bid-ask spread, a measure of market tightness, efficiency, and information asymmetry, widened in response to manipulation. Rational investors may choose to exit the market to avoid trading with a manipulator. These findings suggest that market manipulation is harmful to information-seeking traders, who typically maintain markets efficient. A wider bid-ask spread has also been shown to increase volatility, implying that manipulation increases risk in the stock market. Second, the results of this study indicate that there is no substantiation to support the theory that larger trades are executed at unfavorable prices; thus, this unexpected outcome challenges Easley and O'Hara's (1987) proposition that trade size serves as a proxy for information asymmetry. This study reveals that apart from smaller trades, manipulators can execute large, profitable trades. Third, our results find that illiquidity ratio is not significantly affected by market manipulation. Hence, the market's ability to execute trades without a notable price impact remains largely unchanged even after the manipulation. Lastly, we can conclude that, consistent with previous research, stocks with low liquidity and low volume are more vulnerable to market manipulation.

The study concludes that market manipulation distorts stock markets by negatively affecting the spreads. Since the bid-ask spread is used as a measurement for several aspects of the stock market quality, such as the price of liquidity, information asymmetry and efficiency, the negative impact of manipulation on this particular variable is noteworthy. This study is therefore providing empirical evidence for continued prohibition of market manipulation and has significant implications for individuals and market regulators in developing a comprehensive understanding of the impact of manipulation on market quality.

One of the objectives for conducting this study was a lack of comparable research in mature stock markets such as Sweden. The results, however, were not significantly different from those studies made in less developed stock markets such as Asia (Gerace et al, 2014, Huang & Cheng, 2015), Middle East (Ergün et al, 2021), and Africa (Akinmade et al, 2020). It appears that the impact of market manipulation on stock markets is independent of market development and can affect market quality and efficiency regardless of market maturity. It would therefore be interesting to study further whether market manipulation affects a country's overall economic growth. While this study solely examined the impact of market manipulation on stock market quality, investigating the relationship between manipulation and economic growth could provide insights into whether manipulation primarily affects market efficiency or has wider economic consequences.

To provide a more comprehensive understanding of the effects of manipulative trading on the stock market, additional market quality variables should be explored and included, as it is probable that there are additional factors that have not been accounted for in the models. Moreover, since this study uses low-frequency data, it is recommended that future research should base the market quality measures on high-frequency data to achieve more accurate results. Therefore, we recommend adding explanatory market quality variables, such as order imbalance predictability, intraday market beta, and fundamental value estimators, to the models.

The dataset was limited to 31 cases from 2018 to 2023 as we only examined cases that were prosecuted after the implementation of the MiFID II and MiFIR regulations. To provide a broader perspective on the impact of regulations on market manipulation and market quality, future studies should consider a wider time frame and compare cases before and after the implementation of regulations. Expanding the sample size and scope could result in a more diverse and accurate analysis. Furthermore, a wider range of manipulation schemes could be examined to determine if they have varying effects on the market.

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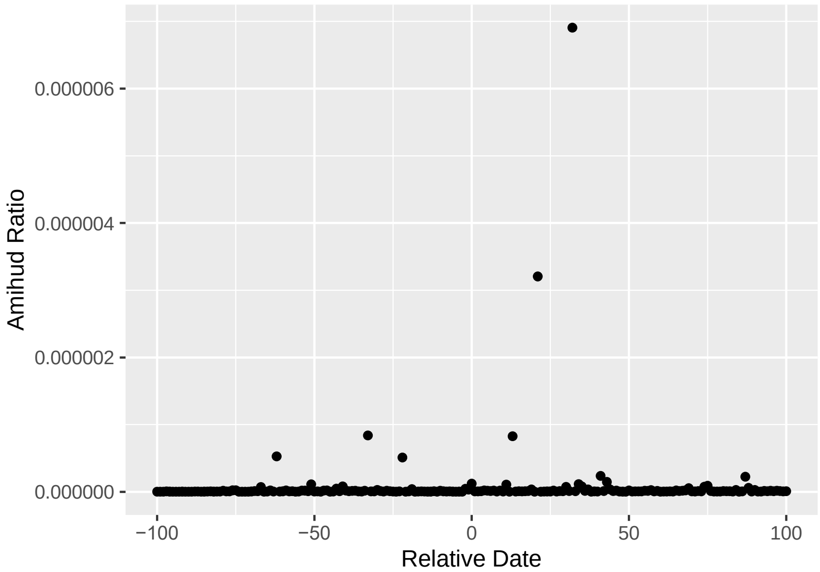
Appendix

Table 4. Net list of manipulated stocks in Dataset

Company Name	Ticker	Manipulation period (YYMMD)
2cureX AB	2CUREX	2018-07-02
Africa Oil Corp	AOI	2021-05-28
Aino Health AB	AINO	2022-01-17 & 2022-02-02
Alligator Bioscience AB	ATORX	2021-02-16
Annexin Pharmaceuticals AB	ANNX	2022-01-21
Artificial Solutions International AB	ASAI	2020-05-04
CirChem AB	CIRCHE	2022-10-18
Clean Motion AB	CLEMO	2019-11-28
Climeon AB	CLIME B	2020-01-13 to 2020-01-14 & 2020-01-28
Clinical Laserthermia Systems AB	CLS B	2019-03-14 to 2019-03-18
Dignitana AB	DIGN	2018-09-19
Doro AB	DORO	2021-05-05
Enersize Oyj	ENERS	2018-03-14
GHP Specialty Care AB	GHP	2019-01-09 to 2019-02-14
H&D Wireless Sweden Holding AB	HDW B	2018-08-01 to 2018-08-27
Heliospectra AB	HELIO	2020-05-12
Inission AB	INISS B	2020-12-28 to 2020-12-30
Ivisys AB	IVISYS	2018-01-29
Klaria Pharma Holding AB	KLAR	2022-03-08 & 2022-03-14 & 2022-03-15
Lauritz.com Group A/S	LAUR	2018-01-17
Maha Energy AB	MAHA A	2019-12-03 & 2019-12-10 to 2019-12-13
myFC Holding AB	MYFC	2019-11-18 to 2019-11-20
Neola Medical AB	NEOLA	2021-09-17
Netmore Group AB	NETM B	2019-03-14
Nexstim Oyj	NXTMS	2021-08-30 to 2021-09-30
Scandion Oncology A/S	SCOL	2021-12-14
SenzaGen AB	SENZA	2020-07-14
Speqta AB	SPEQT	2020-03-13
Studentbostäder i Norden AB	STUDBO	2019-04-04
Torslanda Property Investment AB	TORSAB	2020-04-01
Veg of Lund AB	VOLAB	2022-06-13 to 2022-08-16

Graph 9. Raw data for illiquidity measure and log-transformed data



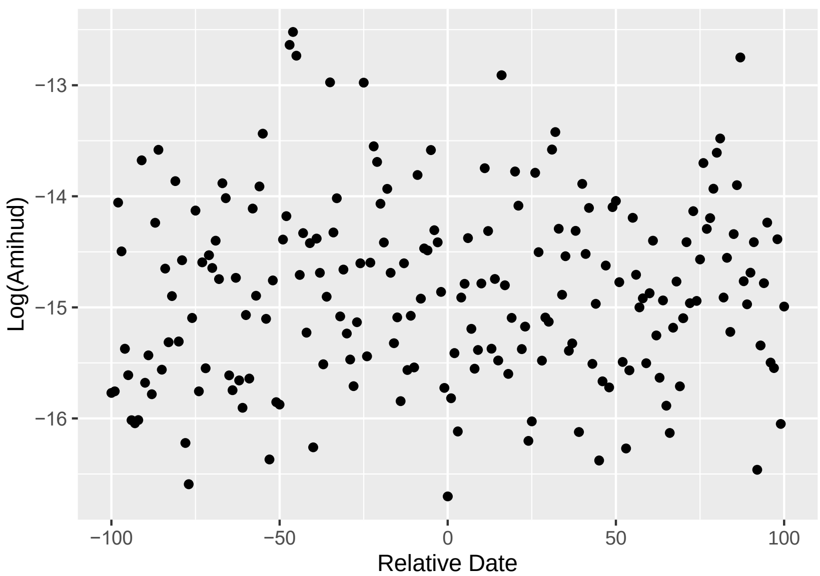


Table 5. Descriptive characteristics of manipulation cases

The table below shows various types of manipulation behavior for the 31 manipulated stocks.

Type of Manipulation	Number of cases
Action based manipulation	20
Information based manipulation	0
Trade based manipulation	11
Total	31

Action based manipulation involves cases of inflating prices and buying shares with the intent to sell them at artificial prices. The cases are mostly small-quantity trading, also known as "printing" (sw: "enpetare"). Trade based manipulation mainly includes "wash trading" cases and the creation of false market signals by increasing trading volume. Information based manipulation was not examined in this paper.

Table 6. Variance Inflation Factors

The following table shows VIF values for checking multicollinearity in the regression models. All values are below five, which implies that there is very little multicollinearity among the independent variables.

	Price Analysis	Quantity Analysis	Illiquidity Analysis
Dummy	1.270735	1.318552	1.316456
PBAS		1.297661	1.325206
Volume	1.803670		1.675922
Volatility	1.593357	1.787085	1.875665
Share Turnover	1.830931	1.463642	1.847652
Illiquidity	1.146060	1.042754	