ERASMUS UNIVERSITY ROTTERDAM

ERASMUS SCHOOL OF ECONOMICS

MSc Economics & Business or

Specialization Financial Economics

A Market-wide Analysis on Short Selling Disclosures, and the Effect of Bans on Liquidity and Volatility

A study within the European Market

Author:	M.B. Nanninga
Student number:	449333
Thesis supervisor:	Dr. J.J.G. Lemmen
Second reader:	Dr. (Vadym) VV Volosovych
Finish date:	April 2023

Preface and Acknowledgements

I would like to thank the Erasmus University of Rotterdam for providing me with guidance during my studies. More specifically, I would like to thank my thesis supervisor Jan Lemmen for providing me with useful insights and comments on this thesis. I would describe the period of writing my thesis with Jan Lemmen as a smooth ride. Moreover, I would like to thank family and friends for supporting me throughout my stay at the Erasmus School of Economics.

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Abstract

This thesis studies EU-regulated net short position disclosures of 14 European countries, including the United Kingdom. The main sample consists of 15,765 net shorted positions throughout the 1st of November 2012 to the 31st of August 2022. We examine the performance of this unique dataset over different event windows, as well as creating equally-weighted and short-weighted value portfolios over a holding period of 31 days. These portfolios are then analyzed using multiple factor models. Based on these two methods of analysis, the results indicate that short sellers are able to gain abnormal returns over a short period of time. Moreover, we examine the effects of short selling bans across France, Italy and Belgium in 2020. To investigate the effect on liquidity we use the Amihud liquidity measure and the quoted bid-ask spread. For volatility we use a 5-day rolling standard deviation of returns based on closing prices, as well as the Garman and Klass volatility measure. We examine the effects on these two measures by providing a Difference-in-Difference model. The results indicate that short selling bans have a negative impact on liquidity. In addition, the results show that volatility decreased for the banned stocks, hence, the ban was actually effective in that matter.

Keywords: Short selling, Net short positions disclosures, Stock performance, Short selling ban, Covid-19, Liquidity, Volatility, EU-regulation.

JEL Classification: G400, G140

1. Introduction

Essentially, there are two types of investors in the financial market: optimistic investors and pessimistic investors. Finding expensive equities in which they anticipate a future decrease in stock prices is the goal of a group of pessimistic investors. These types of investors, also referred to as short sellers, are important to financial markets' efficiency. Short selling was already present before there were financial markets as we know them nowadays. In 1609, Isaac le Maire, a co-founder of the Dutch East India Company (VOC), shorted VOC shares with a group of nine affluent men. For institutional investors like hedge and mutual funds, short selling was a common trading tactic during the 2008 financial crisis. The US Securities and Exchange Commission (SEC) and other regulators temporarily banned short selling in the financial markets to preserve the integrity of the markets in response to the sharp decline in stock prices (Securities & Exchange Commission, 2008). The temporary ban was mainly focused on the prohibiting short selling activities regarding bank and insurance stocks.

At the same time, hedge funds were scapegoated by common people and retail investors for their allegedly harmful participation in short selling. Michael Steinhardt, a well-known hedge fund manager, explained that traders of hedge funds benefit from the pain of others, and that they are targeted in periods like the financial crisis (Zuckerman, 2008). The question that remains is whether short selling regulators should put a crimp on short selling in general. The Dot-Com bubble is another example in which short selling has been restricted by regulators. The adverse effects of short selling restrictions on the market during the Dot-Com bubble is illustrated in a well-known paper by Ofek & Richardson (2003). Pessimistic investors were severely constrained from shorting overvalued firms in the internet industry in the two years prior to the burst which resulted in gains of over 1,000 percent, which then completely vanished after the burst in March 2000. Despite these historic events, short sellers are frequently held accountable for market downturns, which raises concerns regarding speculative trading and market deterioration. In 2020 activist investors voiced their opposition against large, short selling hedge funds. Activist investors from Reddit targeted heavily shorted stocks which lead to short squeezes in AMC, GameStop, and Bed Bath and Beyond. For instance, GameStop Corporation (GME) stock price increased by approximately 1,625% from the 1st of December 2020 to 1st of January 2021. In turn, this led to the forced closure of hedge funds such as Citron Research and Melvin Capital. In times of recession or bearish markets, the discussion surrounding short sales always intensifies. Fortunately, numerous researchers have analyzed the behavior of investors and the impacts of short selling on the financial markets. Some have questioned whether the SEC's implicit goal to halt stock price decreases or even pump stock prices upwards was achieved in the 2008 financial crisis (Beber & Pagano, 2013; Boehmer, Jones, & Zhang, 2013).

Previous research addressed the question of whether short sellers are informed traders (Boehmer, Jones, & Zhang, 2008; Engelberg, Reed, & Ringgenberg, 2012). In addition, studies have shown the effects of short selling bans on price efficiency, liquidity, and volatility (Beber & Pagano, 2013; Chang, Cheng, & Yu, 2007; Saffi & Sigurdsson, 2011). According to the findings of these studies, short selling contributes to making the market more efficient by exposing firms that are overvalued and by correcting market overreactions (Diether, Lee, & Werner, 2009). Since November 2012, all member states have been required to report to the Relevant Competent Authority (RCA) all significant Net Short Positions (NSPs) in shares. This study will examine the impact of net short positions disclosures on the performance of European stocks, as well as the impact that short sale bans in 2020 had on the liquidity and volatility of stock markets in European countries.

Whether those who engage in short selling are good or evil is a pertinent sociological question in financial markets. In other words, what function do short sellers play in the financial markets, and do they contribute to market efficiency? Therefore, our research question is as follows:

What is the effect of short selling disclosures on stock performance, and to what extent do short selling bans impact liquidity and volatility?

The study aims to make important contributions to the existing literature on the effects of short selling on market efficiency and to develop a more thorough understanding on short sellers' behavior. Extensive prior research has examined the role of short sellers in financial markets using short interest and in the presence of short selling restrictions, targeting specific industries. For instance, Beber & Pagano (2013) studied the US short selling ban on financial stocks in 2008. The main focus of this study is to examine short selling disclosures in European countries, by investigating the effect of short selling disclosures on stock returns, as well as the impact of the 2020 short selling ban on liquidity and volatility. Previous contributions on the impact of short selling disclosures in the equity market have been made by various papers (Benhami, van Veldhuijzen, & Schoolderman, 2022; Galema & Gerritsen, 2019; Jank & Smajlbegovic, 2017; Jank, Roling, & Smajlbegovic, 2021; Jones, Reed, & Waller, 2016). Jank & Smajlbegovic (2017) examine the actual performance and trading strategies of informed and sophisticated short sellers. Jank *et al.* (2021) use European disclosure data to examine the impact disclosure requirements for large short positions have on investors' behavior and stock prices. A more recent study compares the short selling ban in France in 2020 during Covid-19 with the permitted short selling in Netherlands (AFM, 2022). They find no significant differences in stock price increases between the French and Dutch market. In addition, for the French banned short selling stock, volatility decreases more than in the Dutch market. This finding stands in contrast to the findings of short selling bans in 2008 (Boehmer *et al.*, 2013). This paper builds upon the previous studies by using a unique dataset of disclosure data. Not many papers have investigated the effects in the European market for the short selling performance, as well as the short selling restrictions in 2020. This paper contributes on the existing literature by examining the performance of net short positions across multiple European countries during different event-windows and adding factor models to the analysis. Also, this study distinguishes itself by using different liquidity and volatility variables when determining the effect of the short selling ban in 2020. This recent short selling ban is considered unique, since the ban targets all industries rather than one specific industry.

This study finds negative Cumulative Abnormal Returns prior to the disclosed net short positions, while post-event we find negative Cumulative Abnormal Returns until 10 days after the event-window. In addition, we find that the negative abnormal returns decrease with regards to the pre-event. Interpreting these results, we can conclude that it appears the findings support the idea that short sellers are informed. For robustness we present multiple factor models in which we examine 31-day equally-weighted (EW) portfolios and short-value-weighted (SVW) portfolios to capture the abnormal returns. The study shows that the three factor model for the EW portfolio achieves an alpha of 0.05% at a significance level of 10%, whilst the SVW portfolio achieves statistical significant alpha's of 0.08% and 0.17% for the three-factor, respectively, four-factor model. All results are in line with the findings of the event study and previous research.

The results on the effects of short selling bans in 2020 across France, Italy, and Belgium are given in the next part of the study. First of all, we find that the bans in these three countries had a significant impact on both liquidity measures. In other words, we find that banned stocks had a more negative impact on liquidity compared to the period before the ban was implemented. With regards to volatility, the results indicate that volatility decreased during the ban period for all stocks in the sample. For the stocks that were banned from short selling, we find that they had an even lower degree of volatility according to the two dependent volatility variables in the period 17th of March 2020 until 18th of May 2020.

The remainder of the paper is divided in multiple sections. In the next section a literature review is provided in which we discuss the concept and rationale of short selling, as well as the transparency rules implemented by the European Union in 2012. Moreover, we will provide previous views on stock performance with regards to shorted stocks and the effects than short selling has had on liquidity and volatility prior to Covid-19. Based on the provided literature in this paper we have come up with three hypotheses that are used to provide an answer on the research question. In the third section this paper elaborates on how the data was collected and which cleansing procedures have been used to eventually come up with a dataset that is quite unique to our knowledge. In section 4 we will provide a description of the methods and techniques that are used to analyze the data with regards to the three hypotheses. This includes an event study and multiple factor models to interpret the performance of shorted stocks in the period 2012 to 2022. Also, we describe the Difference-in-Difference models used to find the effects that short selling bans in France, Italy and Belgium had on liquidity and volatility in financial markets. Finally, we present and discuss the results and provide the reader with a conclusion of this study, which is accompanied by research limitations and future research.

2. Literature Review

Over the past decade, there has been a rise in interest in short selling on financial markets. Events such as the Dot-Com bubble in 2000, the Financial Crisis in 2007-2009, the Pandemic in 2020, and the notorious Reddit army and their short squeezes of 'meme stocks' enhanced interest. The aforementioned events have expanded the academic debate on short selling. The current perception of short selling among regulators, CEOs, institutional and retail investors is ambiguous.

According to Chen *et al.* (2019), one out of every five traded shares in the U.S. equities markets involves a short position, indicating that short selling is a substantial factor and contributes to how the market moves. For example, Scion Capital's Michael Burry is a well-known trader who benefitted from the failures of big financial institutions by shorting subprime mortgage bonds preceding the 2008 financial crisis. This event caused retail investors to become emotional and even turn them into short selling criticizers. According to these critics, short sellers spread fear and false rumors, eroding investor trust in the financial system. Short selling proponents, on the other hand, claim that it improves market efficiency. When traders identify overpriced firms, they can sell short, thereby embedding their unfavorable knowledge into market prices. There is substantial academic literature on short selling that covers a wide range of topics.

This section explains the concepts of short selling, liquidity, and volatility using current literature to provide a clearer grasp of what they are and how they are related to one another.

2.1. An introduction on short selling

Short selling is a trading strategy that allows investors to sell a stock they have not yet purchased. To return the stock to the lender, the short seller must purchase the stock from another market participant. The time between selling the borrowed stock and purchasing the stock is considered the short position's holding period. There is no restriction on the length of time a short sale can be open. The rationale for the short position is the expectation that the stock price will decrease within the (near) future. In practice, short selling is regarded to be more of a risk than investing in stocks. Short sellers face loan recalls and shifting loan fees, in addition to the typical risks that many traders encounter, such as margin calls and regulatory changes (Engelberg, Reed, & Ringgenberg, 2018). Theoretically, prices can reach unlimited heights, whilst, on the other hand, the optimum profit from short selling occurs when the stock price falls to zero. This could lead to involuntary liquidation of the short position as a consequence of a stock loan recall. Along with regulatory- and timing-related hazards, as well as short squeezes, short sellers must consider borrowing costs. Legal or institutional constraints prevent investors from engaging in short selling. In financial economics, these limitations are considered as short sale constraints (Lamont, 2004). Correspondingly, Diamond & Verrecchia (1987) imply that short sellers only engage in short selling when they believe stock prices are expected to decrease to cover the additional costs and risks. However, short selling can be a lucrative trading strategy, and professional investors have a variety of reasons to initiate a short selling position. In addition to speculation, more advanced motives include hedging and arbitrage. Hedge- and arbitrage-seeking investors enter short sales in combination with other financial instruments, such as options and futures (Staley, 1996). According to Dechow *et al*. (2001) short sellers aim to arbitrage a price differential between the stock and debt convertible into the stock. Alternatively short sellers compose arbitrage trading strategies, such as trading pairs trading and index arbitrage. Since short selling is a high-risk activity, sophisticated institutional investors such as hedge funds and investment banks generally employ short selling strategies to mitigate exposure throughout periods of market downturns. Furthermore, informed traders seem to short acquirer shares in stock mergers and utilize the proceeds to buy the target stock the day before the merger announcement (Mitchell, Pulvino, & Stafford, 2004).

2.2. EU-regulation on short selling disclosures

According to previous SEC Chairman Shapiro, short selling can both be harmful as beneficial to the equity market. In 2010 the SEC implemented the alternative uptick rule – also known as the 201 rule – which was designed to restrict short selling when a stock price declines by at least 10% in a single day. The logic behind the alternative uptick rule is that it intends to prevent manipulative and abusive short selling and promote market stability confidence (U.S. Securities and Exchange Commission, 2010). Many academics have examined the effect of restrictions on the equity market. Miller (1977) explains that when investors hold different opinions on a stock and short selling is restricted, only the optimistic investors will participate in the market. As a result, stock prices only reflect the opinions of the most optimistic investors, leading to an overvaluation and eventually followed by lower returns. Moreover, Diamond & Verrecchia (1987) examine the impact of short interest announcements and the adjustment speed to private information. They find that short selling constraints reduce absolute and relative informational efficiency and increased the bid-ask spread, hence decreased liquidity. In other words, the price adjustment to new (private) information slows down in the presence of short selling constraints. Other studies have confirmed these results in other settings (Beber & Pagano, 2013; Chang *et al.*, 2007; Saffi & Sigurdsson, 2011).

In 2011, the European Parliament, Commission and Council reached an agreement on imposing permanent regulations on short selling for all EU-member as of the 1st of November in 2012. The regulation established uniform EU standards for transparency and harmonizes the regulators' abilities in exceptional situations in case of threatening financial instability (O'Sullivan & Kinsella, 2012). This measure was directly applicable in all EU Member States because it passed through an EU regulation, and no national measures were required to implement its provisions. This means that the rules governing short selling have been harmonized across the EU, and the different regulations governing short selling that were formerly in effect by EU Member States were surpassed. According to Regulation (EU) No 236/2012, net short positions must be declared if they reach a threshold of 0.5% or more of a firm's issued share capital and continue to publish for each 0.1% above. Market makers have been exempted from the disclosure rule given that they offer liquidity and decrease volatility in order to stabilize equities markets.

2.3. Efficient Market Hypothesis

For a long time, financial markets were considered efficient, and many economists saw it as the cornerstone of asset pricing. Fama (1970) observed that markets are informationally efficient when prices fully represent all available information, which is also known as the Efficient Market Hypothesis (EMH). The weak form of market efficiency stipulates that current prices fully reflect all public historical information, whereas the strong form of market efficiency argues that all current and past information, public or private, is fully reflected in current prices (Shleifer, 2000). The strong form claims that investors are unable to trade on any type of information that would provide them an advantage. Nowadays, empirical studies on market anomalies cast serious doubts on the notion that financial markets are efficient. These market anomalies have received an ample amount of attention since they demonstrate how investors may benefit from systematic mispricing in financial markets. The understanding that markets are inefficient is founded on the principle that underlying prices do not integrate information but rather market participants' opinion. These anomalies stem from the Behavioral Finance Theory (BFT), which states that irrational investor behavior influences the pricing within financial markets. Meanwhile, there are two building blocks in behavioral finance: limits to arbitrage, which contends that it can be difficult for rational investors to undo the dislocations caused by less rational traders; and psychology, which catalogs the various types of deviations from full rationality that we might expect to see (Barberis & Thaler, 2003).

Previous research indicates that the Efficient Market Hypothesis does not hold true in all instances. Academics find evidence suggesting that a high amount of short interest is related to negative abnormal returns. This issue is addressed in two different hypotheses, known as and the overvaluation hypothesis and the informed trader's hypothesis.

The overvaluation hypothesis is initially stated by Miller (1977) who theorizes that stocks with high level of short interest are overvalued due to various opinions on expected stock returns. Restricting short selling leads to an overvaluation of stock prices as only the opinions of bullish (optimistic) investors are incorporated in the stock prices and those bullish investors typically are holding long positions, whereas bearish (pessimistic) investors are incapable to contribute to the pricing process. Short selling stocks with such conditions is costly, thus, leads to overvalued stocks and reduced stock returns. After the short selling restrictions are lifted, pessimistic investors will short sell the overvalued stocks, possibly leading to a higher level of volatility.

On the other hand, Diamond & Verrecchia (1987) predict that an increase in short selling is followed by an increase in negative abnormal returns. As will be discussed in the subsequent subsection, short sellers are found to be informed. When short selling is restricted it becomes expensive, hence, short sellers that continue to short sell must be informed as they expect future negative abnormal returns. The consensus among academics is that short selling is essentially beneficial to financial markets given that it corrects short-term fluctuations in stock prices. Additionally, short selling restrictions may have significant effects on information aggregation due to their asymmetric impact on investors with positive and negative information (Figlewski, 1981).

2.4. Short selling and stock performance

The role short sellers have within financial markets and the effect of short selling on stock returns has been broadly examined by financial academics. In general, academics find that short selling has positive effects on financial markets.

Miller (1977) examines the effects of short selling restrictions and finds that short selling may improve market efficiencies by tolerating various opinions of investors and the subsequent negative abnormal returns, representing a reduction in potential overvaluation. Diamond & Verrecchia (1987) explore the implications of short selling restrictions on the adjustment speed of prices to private information. They predict that short selling constraints slow down the adjustment of stock prices to negative private information, especially with respect to bad news.

Informed traders are those who possess superior information compared to other market participants. In the sense of short sellers, it is expected that their short sale positions follow abnormal negative returns. Research shows that short sellers are predominantly represented by hedge funds (Jank & Smajlbegovic, 2017). Diamond and Verrechia (1987) argue that short selling is not motivated by liquidity needs as short sellers do not have access to the short sale proceeds, implying that there is relatively a small number of uninformed short sellers in the market, ceteris paribus.

Short sellers are seen as informed investors who enhance price efficiency; thus, prices reflect all available information. Boehmer *et al.* (2008) inspect short sellers and their positions based on NYSE data in a sample period of 2000-2004. They provide evidence that short sellers are well informed and find that heavily shorted stocks underperform lightly shorted stocks annually by a cumulative of 15.6%

on average. Diether *et al.* (2009) propose a portfolio approach which shorts relatively high shorted stocks and holds a long position in relatively low shorted stocks. In their study they use SEC-mandated short sale data from 2005. The constructed portfolio approach estimates positive abnormal returns, indicating short sellers can predict future returns, following the informed trader's hypothesis.

Karpoff & Lou (2010) conduct research on whether short sellers can identify overvalued firms, hence analyzing the informed trader's hypothesis. They measure overvalued firms by making use of a sample of firms that are regulated by the SEC for financial misrepresentation in the sample period of 1988-2005. They find that abnormal short interest steadily rises in the 19 months leading up to the misrepresentation of financial statements. Boehmer & Song (2020) investigate the role of retail short sellers in the period 2010-2016 by analyzing daily and monthly short volumes. Since the role of retail short sellers is not clear in financial markets, they examine whether retail short sellers can be informed. The study shows that retail short sellers significantly predict negative future stock returns, therefore, providing evidence that retail short sellers can exploit public information.

Aitken *et al.* (1998) analyze the market reaction towards short sales on the Australian stock exchange and find negative abnormal returns in the period 1994-1996. Other papers are in line with these results in different sample periods and market settings (Desai, Ramesh, Thiagarajan, & Balachandran, 2002; Figlewski, 1981).

To the best of our knowledge, the consensus of short sellers is that they are well-informed since they identify overvalued firms, and their short holdings result in negative abnormal returns. This has largely been studied in US markets, with a few exceptions in European markets. A notable paper that investigates stock performance following short selling disclosures is Jank & Smajlbegovic (2017). This study focuses on the profitability of short selling strategies employing individual short positions. They argue that such data has yet to be used to analyze the direct performance of short sellers. Following the consensus of short sellers being informed traders and using European individual short sale position, this paper proposes the following hypothesis:

H1: European short selling disclosures have a negative impact on stock returns (in the short run)

2.5. Short selling effects on liquidity and volatility

Previous studies have examined the effects of short selling bans on market liquidity and volatility. Liquidity refers to the market's relative capacity to convert a stock into cash, taking into account the associated transaction costs. Liquidity is determined by proxy indicators including trading volume, bid-ask spread, and the Amihud measure, among others. In general, liquidity is regarded as an essential indicator in stock selection.

Primarily, Diamond & Verrecchia (1987) show the effects of restrictions on short selling on stock prices and liquidity. Restricting short selling reduces liquidity, proxied by the bid-ask spread, due to the reduced number of stocks for sale.

Daouk & Charoenrook (2005) look at the effects of short selling restrictions on liquidity and volatility using data on short selling restrictions across 111 countries within a sample period of 1969-2002. It is mentioned that most empirical studies use short selling constraints in the US stock market and apply various measures of short sale constraints. The study indicates that aggregate returns are less volatile, and liquidity is higher when there are no short selling bans, especially in bear markets.

Beber & Pagano (2013) examine the effects of the imposed short selling ban in the 2008 financial crisis on liquidity and price discovery. The research discovers that the short selling ban during this period had adverse effects on stock liquidity, especially for small-cap stocks and those which had no options listed. Moreover, it slows the price discovery period in bear markets, meaning stock prices slowly return to their fundamental value. In accordance, the 2008 short selling restriction did not halt the reduction in price of financial stocks; in fact, prices dropped significantly during the two weeks that the ban was in place before stabilizing once it was repealed (Battalio, Mehran, & Schultz, 2012). Figure 1 demonstrates that in the period following the 2008 short selling restrictions, the median bid-ask spreads were wider for financial stocks that were subject to a ban than for stocks that were not. This is true for all major economies across the world. Hence, it would appear that short selling increases liquidity and reduces transaction costs for investors.

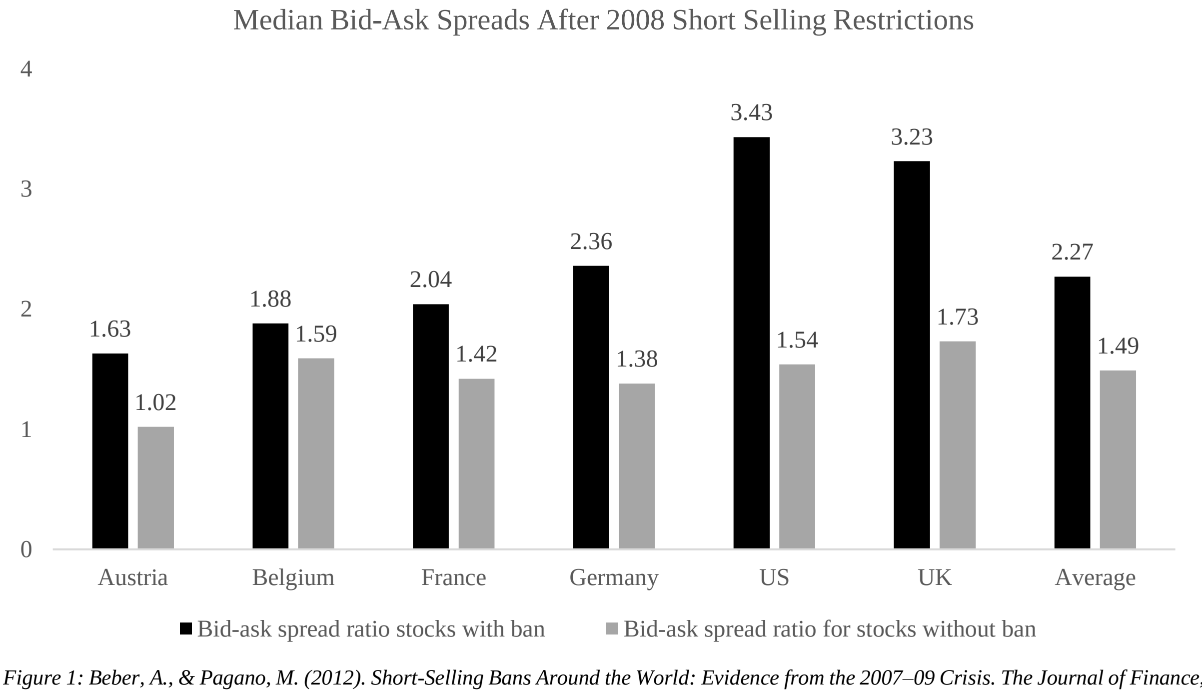

Figure 1: Beber, A., & Pagano, M. (2012). Short-Selling Bans Around the World: Evidence from the 2007–09 Crisis. The Journal of Finance, 343-381.

Jones *et al.* (2016) contribute to the existing literature on short selling by measuring the market-wide effects due to changes in disclosure regimes. Disclosure regimes are described as the pan-European disclosure regime, where any short seller with a short position exceeding 0.5% of the outstanding shares must be disclosed to the relevant RCA. In their study on market-wide effects they follow the informed trader model, which estimates the negative effects of short positions disclosures on shorting activity and increases liquidity (DeMarzo, Fishman, & Hagerty, 1998). Specifically, they find a statistically significant reduction in the bid-ask spread of 41 basis point, suggesting a rise in liquidity.

To contribute to the prior literature in US and European markets one would expect that short selling bans have a negative impact on liquidity. Hence, the following hypothesis is constructed:

H2: European short selling bans have a negative effect on liquidity

Short sellers are often scapegoated for volatility in the market, especially in bear markets.

Miller (1977) states that theoretically in times of uncertainty there are various opinions on future stock returns. Restricting short selling will lead to an overvaluation of stocks, because only the opinions of bearish (optimistic) traders are incorporated in the stock prices. Such investors typically hold long positions in stocks.

Diamond & Verrecchia (1987) explain that short selling constraints lead to a market in which only informed traders are active as they know when the risks and costs of short selling are smaller than the expected return of their short sales. Both papers implicate that short sale restrictions worsen the market quality, therefore increasing volatility.

According to Daouk & Charoenrook (2005), when short selling is permitted, aggregate stock returns are less volatile. In addition, Jones *et al*. (2016) question whether short selling restrictions in European markets are associated with an increase in price volatility measured by the difference between the high and low transaction prices divided by the volume of the stock. According to their research, volatility increases during this period of restriction on short selling. Other studies have shown a rise in volatility in the US markets during the short selling ban of 2008 (Boehmer *et al*., 2013; Bris, 2008).

The vast majority of academic studies address the impact of short selling in extreme market conditions, such as short selling bans imposed as a result of a market crisis. Among the reasons why a great deal of studies on short selling are conducted under extreme conditions is to gain a better understanding of how markets perform with regards to price efficiency, liquidity, and volatility. In contrast, Ho *et al.* (2022) examine the effect of short selling on volatility in times of non-extreme markets with Australian data in the sample period of 2009-2011. During this period there were bans initiated on short selling in the Australian markets. In their paper they find that short selling has a small positive effect on volatility during normal market conditions.

To contribute to the prior literature in the US and European markets, we would expect that short selling bans have a negative effect on volatility within the Covid-19 sample period. Therefore, we construct the following hypothesis:

H3: European short selling bans have a negative effect on volatility

More recent studies have shown the impact of short selling bans on liquidity and volatility. The AFM report "French and Dutch market authorities publish analysis of impact temporary French short sell ban in 2020" focuses on the impact of short selling restrictions between the 17th of March and the 18th of May in 2020. This historical period is quite unique because the countries that implemented bans for stocks made no distinction between industries, whilst this distinction was in fact present during the short selling restriction which was enacted in response to the 2008 financial crisis. During the 2008 ban only the financial stocks were banned for short selling. In the AFM analysis on the Dutch and French market, they found mixed results, such as (1) an increase in returns, with no significant difference between the two markets; (2) lower volatility on French equity securities, with a more pronounced effect on large caps; and (3) the absence of a significant deterioration in the liquidity available at the best bid and offer prices between the French and Dutch markets (AFM, 2022). These are effectively interesting findings and perhaps carefully suggest a contradiction to a considerable amount of previous literature that states short selling bans are detrimental for market efficiency. In addition, the paper uses actual order book depth to measure liquidity, which is a method that could be considered most robust. Although this data is not available for this study and many other papers. On the other hand, Siciliano & Ventoruzzo (2020) studied the effects of short selling bans on 14 European countries, including the United Kingdom. In their study they examine the impact of the short selling bans in 2020 on liquidity and volatility following COVID-19. According to their research short selling bans are associated with lower liquidity.

3. Data

The data section of this paper provides a thorough overview of the data collection procedure, as well as descriptions of data preparation and cleansing methods. The main purpose of the data section is to provide the reader with an understanding of the used data sample for the multiple analyses provided in this paper. Additionally, it clarifies the validity of the study and the limitations of the data set. This paper's data sample is used to test hypotheses and justify the answer to the research question.

3.1. Data background

The 2008 financial crisis raised the awareness of national competent authorities across several European Unions' (EU) member states. Throughout this crisis, countries were forced to implement emergency measures, such as restrictions on short sales. Because of the financial instability caused by this crisis, EU countries desired greater transparency and a coherent legal framework. A non-harmonized approach, on the other hand, would limit the effectiveness of such measures and could lead to regulatory loopholes, and add costs and challenges for investors. As a result, the European Commission found it preferable to have a unified short selling legislative framework across the EU. The EU decided in November 2012 that all Member States must oblige the threshold for the notification of all significant net short positions in shares to the Relevant Competent Authority (RCA). According to article 6 paragraph 2 in Regulation (EU) no 236/2012, in principle net short positions must be published when they reach the threshold of 0.5% or more of the issued share capital of a firm and continue to be published for each 0.1% above, although before February 2022 this threshold was equal to 0.2% instead 0.1%. Net short positions are revealed individually for each country on the national authorities' websites, and they apply to all stocks whose principal trading location is within the EU (Jank, Roling, & Smajlbegovic, 2021). Moreover, in the Netherlands, for example, within the notification process it is required that the notification form is received by the AFM not later than 15.30 (CET) on the day after the day the position was issued. As a result, there is still a one-day lag before the data becomes public. Another consideration is that the AFM rounds net short positions to two decimals. That means if a net short position is actually 0.4599%, it is rounded to 0.45%.(The Netherlands Authority for the Financial Markets, 2015). The European Securities and Markets Authority (ESMA) underlines the significance of short selling. Without diminishing the benefits that short selling offers to the financial markets, the ESMA seeks to reduce the consequences and risks associated with it. Consistent with other studies, we examine a sample of public disclosures across EU countries, including the United Kingdom. Previous studies have conducted a sample of public disclosures from all 28 EU Member States through 2013 respectively 2014 (Jank & Smajlbegovic, 2017; Jones et al., 2016). Although the sample excludes some EU countries due to unobtainable or lack of data. In addition, The United Kingdom is also considered in the sample, since the United Kingdom is a major economy within Europe for which there is plenty of short selling and stock data. Nonetheless, the United Kingdom exited the European Union in 2020. This has no negative implications for the dataset.

3.2. Data collection and cleansing procedure

For the study we obtain net short positions data from the Relevant Competent Authorities for numerous member states, including the United Kingdom. For 19 member states the disclosure data is retrieved from the 1st of November 2012 until the 31st of August 2022. The dataset discloses information on the position holder, the net short position, the disclosure date, as well as the entry, change, and exit of the net short position. Moreover, the database provides the International Securities Identification Numbers (ISIN) that uniquely identify a certain security of an issuer. The position holders are known as the short sellers and the issuers are known as the disclosed firms. The disclosure data is matched with the COMPUSTAT database to specify the industries in which the disclosed firms are active. The dataset is manually updated, since for certain disclosed firms there have been name-, ISIN- or listing changes within the sample period. The raw sample through the sample period consists of approximately 294,636 recorded net short position disclosures across 19 member states. For the relevance of this study, we then employ a data cleaning process. First, we select net short positions at the entry date. This means that this paper does not observe net short positions held by a holder other than the initial position held in a particular firm. The rationale for this is that we anticipate that the first net short position of a holder will be the most material and significant compared to subsequent positions in the same firm. For instance, the initial position reflects the primary decision of a short seller to initiate a short position, which may provide insight into the holder's market sentiment towards a company or its stock. In addition, for the analysis of performance, we consider only unique positions; consequently, subsequent positions are once again irrelevant. Nonetheless, this could be a subject for future research. This also means that we do not evaluate the stock's performance and its effect on liquidity and volatility over the holding period. Subsequently, we match the dataset with daily stock-level data from Refinitiv Eikon / Datastream for the net shorted positions at entry date. All stock-level data is provided in Euros. Each net short position is matched with the leading market index of the country in which it is listed. For instance, the FTSE 100 is used for the United Kingdom and the AEX for the Netherlands. Following Bessler & Vendrasco (2021), the net shorted positions that are considered penny-stocks are excluded to avoid potential biases that are associated with illiquidity. By excluding stocks that are priced less than EUR 1, we avoid biases due to low stock prices and high bid-ask spreads. Low priced stocks, less than EUR 1, are traded at a low frequency, meaning they have a lower liquidity than higher priced stocks. Other concerns among penny stocks could be limited information or high volatility. Lastly, we exclude duplicates, zero values in net short positions, and observations that are based in Czech Republic, Greece, Hungary, Iceland, and Luxembourg as these only account for 36 observations all together. Eventually, after cleansing the dataset we obtain an initial sample of 15,765 net shorted positions for the analysis of stock performance.

Table 1: Descriptive statistics

Country	Observations	Average disclosures	Average NSP	Max NSP
AT	147	4.93	0.87%	21.00%
BE	273	6.62	0.51%	2.28%
DE	4,150	20.74	0.75%	6.50%
DK	1,565	25.02	0.21%	3.72%
ES	458	7.85	0.50%	2.63%
FI	552	28.56	0.84%	7.87%
FR	1,338	10.71	0.51%	2.74%
IE	59	4.31	0.61%	1.72%
ITA	796	7.33	0.60%	16.57%
NL	712	16.76	0.63%	5.18%
PL	131	4.36	0.51%	1.50%
POR	69	5.83	0.51%	1.32%
SE	1,547	10.76	0.64%	4.16%
UK	3,968	8.35	0.51%	8.44%
Total	**15,765**			

Note: The average disclosures are the average number of short positions on an issuer. Average NSP and Max NSP are all in percentages of issued share capital.

Table 1 demonstrates that the average number of disclosures per issuer varies by country, ranging from 4.31 to 28.56. In Finland, Denmark, and Germany, the average number of disclosures is relatively high, and even in the Netherlands, the average number of disclosures is considerable at 16.67. In addition, we find unusual high max NSP in Austria (21.00%) and Italy (16.57%), whereas the rest of the data ranges between 1% and 9%, indicating that short sellers disclose a position between these values market-wide. When interpreting the results in later sections, the reader must take into account that the sample consists primarily of net short positions issued in Germany and the United Kingdom (approximately 51.00% together), followed by Denmark, France, and Sweden.

Table 3 displays the distribution of net shorted positions categorized by industry and country. The table demonstrates that most nations short manufacturing stocks. Additionally, the United Kingdom discloses a significant number of short positions in the services industry. In the agriculture, forestry, and fishing industries, countries do not frequently hold net short positions.[1]

3.3. Daily stock price data

To analyze the performance of net shorted positions, we use daily stock prices of the shorted stocks in the data sample which are provided by Refinitiv Eikon / Datastream. From the daily stock prices we can estimate returns for the market model used to predict the normal returns in an event study. In this

[1] For a division of all industries, one could go to the following: https://www.sec.gov/corpfin/division-of-corporation-finance-standard-industrial-classification-sic-code-list

paper we proxy the markets' returns by using the leading market index of each EU country, which are available for the full sample period between 2012-2022. The daily stock returns and daily market index returns are used for the market model to analyze the performance of the shorted stocks. To enhance relevance of this study we construct a multi-factor model following Jank & Smajlbegovic (2017). The sample consists of European stocks, thereby factor data is obtained from the AQR database[2] instead of the Kenneth and French library, as this database provides international factor data besides US data. Moreover, Jank & Smaljbegovic (2017) used the AQR database as well. The AQR database considers the following factors: daily market returns in excess of one-month T-bills (MKR-rf), Small-Minus-Big (SMB), High-Minus-Low (HML), Momentum (UMD), and Betting-Against-Beta (BAB).

3.4. Coarsened Exact Matching sample

For the analysis on short selling bans in 2020 we use a Difference-in-Difference model for which a matched sample is constructed. In this study we use Coarsened Exact Matching (CEM) instead of Propensity Score Matching (PSM) as this method is considered most plausible for the research. According to Qin (2011), CEM produces higher multivariate balance and consistently less biased effect estimates than PSM and Genetic Matching (GM). We obtain data of short selling bans for three countries: France, Italy, and Belgium. We have data on 11 other countries that did not implement a short selling ban. We use stock data for the period 17th of January to the 17th of July of 2020. This period is divided within three sub-periods in our analysis, which are the pre-ban period from the 17th of January until 16th of March; the during-ban period, which is from the 17th of March until the 18th of May; and the post-ban period, which is from the 19th of May to the 17th of July. Each period has a duration of approximately 2 months. The sample is matched on average market capitalization and Fama French 12-industry classification, where the SIC codes are mapped into 12 industries.[3] The consumer durables and non-durables are combined, hence, resulting in 11 industries. Table 4 provides a comparison between the unmatched and matched sample. The unmatched sample consists of 1,544 firms of which 666 firms are firms that are banned during the short selling ban across three countries (France, Italy, and Belgium). The matched sample consists of 930 firms of which 465 firms are banned during the short selling ban.

[2] https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Daily
[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html

Table 4: Unmatched vs matched sample using Coarsened Exact Matching

Fama-French industry code (11 industries)	Unmatched Sample			Matched Sample		
	0	**1**	**Total**	**0**	**1**	**Total**
Consumer (non-)durables	66	73	139	50	50	100
Manufacturing	132	72	204	59	59	118
Oil, Gas, and Coal Extraction and Products	12	9	21	5	5	10
Chemicals and Allied Products	27	18	45	12	12	24
Business Equipment	140	106	246	66	66	132
Telephone and Television Transmission	24	12	36	10	10	20
Utilities	23	20	43	14	14	28
Wholesale, Retail, and Some Services	81	47	128	32	32	64
Healthcare, Medical Equipment, and Drugs	55	40	95	30	30	60
Finance	144	130	274	100	100	200
Other	174	139	313	87	87	174
Total	**878**	**666**	**1544**	**465**	**465**	**930**

Note: When a firm is banned, it equals 1, while unbanned firms equal 0. The banned firms are from France, Italy, and Belgium, as these countries are the only ones who implemented a ban in 2020 and for which data was publicly available. The unbanned firms are from all EU member states extracted from the original dataset. The unmatched sample comprises the total number of firms within the dataset prior to coarsened exact matching.

Table 6 in the Appendix provides a two-sample t-test to examine whether there are differences in the natural logarithm of average market capitalization between the banned and unbanned stocks. The idea of this method is to test whether there is a statistically insignificant difference between the mean values of natural logarithm of average market capitalization for banned and unbanned stocks. This is done to see if the matched sample and the unmatched sample are comparable. From Table 6 in the Appendix we can conclude that the difference in firm size between the banned and unbanned stocks is insignificant. In other words, the sample has correctly been matched for further analyses. As for the Difference-in-Difference analysis, which is explained in the methodology section, one wants to start from the same trend (changes in levels) or same level. Table 6 documents evidence that the Coarsened Exact Matching approach is sufficient, as the p-value is statistically insignificant. For the matched sample, we find a p-value equal to 0.86, which is higher than the significance level of 0.05. Hence, this supports the idea that there is no statistically significant difference between the means of the banned and unbanned group for natural logarithmic average market value within the matched sample. The reader should understand that further understanding on the Coarsened Exact Matching approach, one should read the methodology section.

3.5. Measurement of liquidity

For the analysis on the effect of short selling disclosures on liquidity, we obtain bid- and ask prices for all net short positions to estimate the quoted bid-ask spread. The quoted bid-ask spread measure is calculated as following:

$$Quoted\ Bid - Ask\ Spread_{it} = \frac{Ask_{it} - Bid_{it}}{\frac{1}{2}(Ask_{it} + Bid_{it})}$$

Where the bid price is the highest price an investor is willing to pay to buy a specific stock, whereas the ask price is the lowest price a seller is willing to sell a particular stock. The quoted bid-ask spread is estimated at time (t) for stock (i). In principle, when the coefficient of the measure is positive it means that stock (i) is less liquid on day (t), vice versa. The quoted bid-ask spread is used in other studies for the effect of short selling on liquidity (Beber & Pagano, 2013; Jones et al., 2016). To normalize the quoted bid-ask spread, we take the square root of the variable. The square root of the quoted bid-ask spread is taken for further analysis as we find that the variable is skewed to the right. This should reduce heteroscedasticity of the residuals. Oddly, the sample consists of negative values for the quoted bid-ask spread sample, which could be explained by misrepresentation. Therefore, the spread is winsorized at a 1%-level.

In addition, we follow Jones *et al.* (2016) and include the Amihud illiquidity measure, which is a financial measure to assess the illiquidity of a stock. The Amihud measure is considered to convey the absolute value of stock return and be a more direct measure of liquidity than, for instance, turnover because it incorporates price changes and transaction costs. In addition, many academics prefer this method over others, such as order book data, on the basis that this data is considerably more easily obtainable while remaining accurate. The Amihud illiquidity measure represents the average ratio of absolute daily return to the dollar volume. As it is an illiquidity measure, we take the inverse to interpret liquidity. The Amihud estimate is calculated as follows:

$$AMIHUD_{it} = \frac{1}{1/N \sum_{t=1}^{T} \frac{|R_t|}{P_t * VOL_t}}$$

Where $|R_t|$ represents the absolute daily return of stock on day (t) and $P_t * VOL_t$ represents the trading volume on day (t). The reciprocal of the Amihud measure should be interpreted as following: when the coefficient of the measure is negative it means that the stock (i) is more illiquid on day (t). To normalize the reciprocal of the Amihud measure, we take the natural logarithmic of the variable.

3.6. Measurement of volatility

For the examination of volatility we use historical volatility, also known as the rolling standard deviation of returns or close-to-close volatility, which is used considerably in previous studies to measure volatility. In principle, volatility is defined as an indicator that captures the rate of changes in stock prices. The close-to-close volatility is calculated by using logarithmic returns of inter-day closing stock prices, hence, disregards the intraday movements of stock prices, as well as the opening gaps that often occur in stock prices. This measure is considered one of the simpler proxies for volatility, although it is still considered efficient for academic research. Studies that examine the effect of short selling on volatility have used different rolling standard deviations. In the study by AFM (2022), they use a historic volatility measure based on the 5-day rolling standard deviation of returns, whilst Beber & Pagano (2013) and Siciliano & Ventoruzzo (2020) use a 20-day rolling standard deviation of returns. In this study we will be using a 5-day rolling standard deviation of returns. The estimation of the historic volatility measure is as following:

$$\sigma_{it} = \sqrt{\frac{N}{n-2}\sum_{i=1}^{n-1}(r_i - \bar{r})^2}$$

$$\bar{r} = \frac{r_1 + r_2 + \cdots + r_{n-1}}{n-1}$$

Where, r_i is considered the logarithmic returns based on closing prices, and N is the number of closing prices in the sample period for stock (i), and n is the number of historical days used to estimate the rolling standard deviation of returns for stock (i). The volatility measure is named Vol5 in the regression models.

Alternatively, we provide a second measure for volatility to find robust results in the analysis. The second measure that is used is known as the Garman and Klass historical volatility measure, which considers historical closing, low, and high prices (Garman & Klass, 1980). This study uses the previous day closing price as opening prices, consequently, it still does not fully reflect the opening gap. The opening price is an essential factor for the estimation of volatility, as one should consider that financial markets are most active at the beginning of the day because of the execution of pending market orders. On the other hand, the estimation captures the intraday high and low stock prices. In light of this, the measure is suggested to be more efficient than the close-to-close volatility. The improved performance measure of volatility in comparison to the close-to-close volatility arises from data compression. For the interpretation of this measure, one should keep in mind that it should not be interpreted as exact values of volatility; thus, it is still a noisy estimator. The calculation of the Garman and Klass volatility is as following:

$$\sigma = \sqrt{\frac{N}{n}\sum\left[\frac{1}{2}\left(log\ \frac{H_i}{L_i}\right)^2 - (2\ log\ (2-1)\left(log\ \frac{C_i}{O_i}\right)^2\right]}$$

Where N is the number of closing prices, n is the number of historical prices in the sample for stock (i), H_i and L_i are respectively the intraday high and low prices, and C_i and O_i are the closing price and opening price (previous day closing price).

3.7. Control variables

For the analysis on liquidity and volatility we add some other control variables to the model that is supported by previous literature. Following European Securities and Markets Authority (2022) and Siciliano & Ventoruzzo (2020), we add a stringency variable as a country control variable to the models. This variable is a composite measure constructed with the use of nine response indicators encompassing for instance school closures, workplace closures, and travel bans during Covid-19.[4] The measure is scaled between a value of 0 to 100, with 100 being most stringent. In addition, we add a lag variable for the return of stock (i). This variable contains the return of the previous day. This variable is added to the model as it helps to control for the potential effect of previous returns on the dependent variables. Following European Securities and Markets Authority (2022), we add the lagged return of the Euro Stoxx 50 volatility index ($VSTOXX_{i, t-1}$) as a control variable at a European level. This helps to control for effects that are broader than specific country effects, such as macro-economic effects on an EU-level. We use this volatility index because it measures the implied volatility for options on a European level, for which data is easily and publicly available. We also control for potential influences of a firm's value or growth by adding a book-to-market (B/M) variable to the models. In addition, we follow Beber & Pagano (2013) by adding stock-level Fixed Effects to certain models on liquidity and volatility. Stock-level characteristics such as analyst coverage, debt-to-equity (D/E), and return on assets (ROA). Analyst coverage is a dummy variable that equals one when a stock is covered and zero when a stock is not covered. This data has been extracted from I/B/E/S, which collects and aggregates the various estimates made by stock analysts. All non-dummy stock-level characteristics are winsorized at a 1%-level to minimize the effect of outliers. The descriptive statistics for dependent and independent variables can be found in Table 7. The descriptive statistics for stock-level Fixed Effects can be found in Table 8 in the Appendix.

[4] https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

Table 7: Descriptive statistics of Coarsened Exact Matching sample

Variable	Unbanned Sample (ban = 0)				Banned Sample (ban = 1)			
	N	**Mean**	**Median**	**SD**	**N**	**Mean**	**Median**	**SD**
Amihud liquidity	56,267	18.13	18.24	2.79	54,706	18.14	18.05	2.92
Quoted bid-ask spread	58,417	0.03	0.03	0.03	59,256	0.04	0.03	0.03
Vol5	58,592	0.52	0.42	0.40	57,505	0.45	0.35	0.39
Garman and Klass vol	56,127	0.52	0.44	0.31	56,880	0.45	0.38	0.30
B/M	53,423	-0.68	-0.60	1.00	57,523	-0.44	-0.36	0.82
Stringency	58,452	48.24	59.72	28.89	59,365	56.28	67.59	30.43
$R_{i, t-1}$	57,528	-0.03	0	4.23	58,439	-0.07	0	3.74
$VSTOXX_{i, t-1}$	57,324	1.37	-1.33	11.29	58,435	1.31	-1,43	11.26

Notes. This table provides the descriptive statistics for all dependent and independent variables for the Coarsened Exact Matching sample consisting of 930 firms. N is the number of observations in the sample. The Amihud liquidity measure is natural logarithmic value of the reciprocal of the Amihud illiquidity. The quoted bid-ask spread is square root of the quoted ask-bid spread. Vol5 is the 5-day (weekly) rolling standard deviation of return using closing prices. The Garman Klass Vol variable is the 5-day rolling standard deviation of return using open, close, high, and low prices. The B/M value is the natural logarithmic value of the book-to-market ratio. The stringency measure is a value between 0 and 100, where 100 is most stringent. The $R_{i, t-1}$ is the lag of the return of stock (i) in decimals. $VSTOXX_{t-1}$ is the lag of the return of VSTOXX in percentages.

Table 7 documents descriptive data for all dependent and independent variables in the sample period 17th of January 2020 through the 17th of July 2020. This table describes the summary statistics for the unbanned sample, which are stocks that are not banned during the ban period from the 17th of March 2020 to the 18th of May 2020. In addition, it shows the summary statistics for the stocks that were banned during the ban period in 2020 in the second column of Table 7. We find that the amount of observations differ across the variables, since we observe closed markets on vacation days and lack of data for those stocks (missing values). Nonetheless, the difference between groups (unbanned vs banned) in terms of the number of observations for each variable appears to be non-material.

Table 7 displays fairly equal values for all given variables across the means, medians, and standard deviations between the groups. The liquidity measures (Amihud liquidity and quoted bid-ask spread) have lower mean values for the unbanned sample than for the banned sample, although this difference seems to be minimal. The volatility measures (Vol5 and Garman and Klass vol) show higher mean and median values in the unbanned sample compared to the banned sample. The book-to-market ratio (B/M) seems to be more negative in the unbanned sample, meaning that these firms have more liabilities than assets, in relative terms, compared to the banned sample. In addition, the mean stringency is higher for the banned sample (56.28) compared to the unbanned sample (48.24), meaning that the countries France, Italy, and Belgium were more stringent than the whole sample of 14 countries. The reader should consider the fact that the stringency variable captures nine different metrics[5]. Moreover, the creators of the stringency index emphasize that it merely measures the stringency of government

[5] Nine metrics captured by stringency index: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls

policies. It neither measures nor implies the suitability or efficacy of a country's response. Finally, we find that the mean lagged return of the unbanned sample is less negative than the banned sample, which is quite interesting, since short selling was not allowed for a period in the banned sample, whilst this still was allowed in the unbanned sample.

Table 8 in the Appendix shows descriptive statistics for the stock-level Fixed Effects. It shows that the mean return on assets (ROA) is higher for the unbanned sample (2,89%) than the banned sample (0.70%), meaning that the firms in the unbanned sample on average seem more efficient in converting their assets into net income. The standard deviation for the ROA is higher for the unbanned sample (12.04%) in comparison to the banned sample (11.11%), meaning more variability in the variable, hence, more extreme values.
Table 8 demonstrates that on average the banned stocks are more covered by analysts and that the firms have a higher leverage ratio.

Figure 2 shows a difference between the average of the stringency measures (compiling the stringency index) between countries that banned short selling for a period in 2020 (France, Italy and Belgium). Moreover, it demonstrates that Italy was quick to implement numerous stringent measures to control for Covid-19. In addition, we discover that France was the second country to implement stricter measures, while Belgium was the last one compared to the other 2 countries. Considering the observations shown in figure 2, Italy was the country where the pandemic was reported first in Europe, while other countries around the Alps followed (such as Austria and France). Strictness elevated for all countries around the 18th of March 2022, since the figure shows an increase in stringent measures for all countries. This is in line with the implementation date of short selling bans in the three countries.

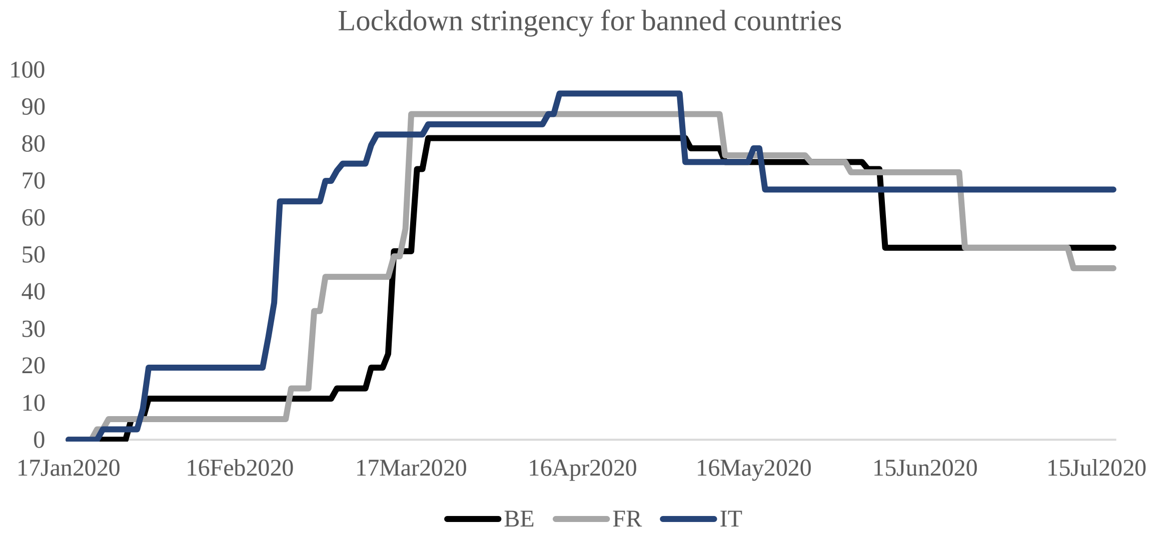

Figure 2: banned countries are those who banned short selling for a period in 2020 due to Covid-19

One of the most important assumptions for linear regression models is that the explanatory variables are not correlated, also known as multicollinearity. Multicollinearity refers to the presence of highly correlated explanatory variables in a regression model, in which case it is very hard to measure their individual impact on the dependent variable of a regression model. This leads to a reduction in predictive accuracy and makes it difficult to correctly interpret the effects of the individual explanatory variables. Hence, this paper examines whether there is multicollinearity between the independent variables. In Table 17 in the Appendix, we first look at the dependent variables to check whether we can check for some correctness of the measures. We find that the liquidity measures, Amihud liquidity and bid-ask spread, are quite strongly negative correlated (-0.672). This is not a problem for the regression models in this research as not both measures will be implemented in the same model. Next, when the Amihud measure is lower, it indicates that the stock is less liquid. The bid ask spread should be interpreted when it is lower, it means the spread is tighter and that the stock is actively traded. In other words, a tighter bid-ask spread means that the stock is more liquid. The pairwise correlation between the volatility measures is strongly positive (0.699), which is sound as the sign of both measures is interpreted the same. A relatively higher coefficient means that the volatility is higher for a stock. Next, we find that stringency is strongly negatively correlated (-0.866) with the pre-period, meaning that in the pre-period there was almost no stringency. This is in line with what one would expect since the stringency measures began around mid-March for most EU countries. Following this association, the pairwise correlation between during and stringency is strongly positive, which in fact is also understandable. Lastly, we find a low negative correlation (-0.406) between the lagged return variable of a stock and the lagged return variable of VSTOXX. This means that when the stock return of the previous day increased, the lagged return of VSTOXX decreased. As we do not find any strong correlation between de explanatory variables, except stringency, we argue that there is no multicollinearity in the regression models.

4. Methodology

The methodology section of this research consists of methods used to conduct an examination on the effects of short sale disclosures on stock performance and the effects of the short sale bans on liquidity and volatility. The research design and statistical methods used are explained thoroughly and based on previous literature. This section serves as the guidance for the research and the methods are meant to provide the reader a picture on the reliability of the study and the limitations of the methods. The methodology of this paper aims to justifiably test hypotheses and support the answer to the research question. In the first two subsections the methods on examining the performance of disclosed net short positions are provided to test the first hypothesis. The third subsection will provide a clear understanding on the method that is used to examine the effects of short selling bans on both liquidity and volatility to test the second and third hypothesis.

4.1. Time series market model approach: Effect of short selling disclosures

The research employs an event study approach to examine the effect of short sales disclosures on daily stock returns during the evaluation period. This method is used to test the first hypothesis:

H1: European short selling disclosures have a negative impact on stock returns (in the short run)

In general, an event study should be interpreted as measuring the effect and significance that a certain economic event has on stock returns. Translating this to our research, an event study is provided to inspect the effect short selling disclosures have on stock performance and during which period the effect is strongest and significant. The research limits itself to unique entries and excludes subsequent net short positions by a holder in the same issuer, as well as exit observations. Unique entries are stocks that are shorted for the first time on a given day. This means the event study excludes net short positions that are not entry positions by a certain short seller.

Following MacKinlay (1997), we use the market model for the event study which captures the abnormal returns during the test period for similar economic events. The market model is calculated as following:

$$R_{it} = \alpha_i + \beta_i R_{mt} , t = 0,1,2, \dots , T$$

Where R_{mt} equals market return, which is the return of the leading index per country. t represents the number of days and i represents the firm.

When markets are in fact efficient, one would expect that the abnormal returns are equal to zero. The market model is the most pronounced method for an event study and examines the relationship of a stock's returns and a given market index. The first step in the process of an event study is to define the periods, such as the estimation period and the event period. The event period is defined as the days before and after the specific event. In this study we examine different event periods ranging between [-6; +30]. This is in line with the event period that is used in the academic paper on the effect of short selling disclosures by Jones *et al.* (2016).

The estimation of the parameters in the model are derived from a time series regression within an estimation period. This period is defined as the preceding period of the event period and considers controlling for unrelated events. When unrelated events occur during this period, it may bias the parameters. An estimation window normally ranges between 250 days to 30 days preceding the event

(Aktas, de Bodt, & Cousin, 2007). For this analysis, an estimation period of 71 days is employed, ranging between [-100; -30]. This period is chosen as this is within the range that previous literature normally uses. According to Aktas *et al.* (2007), typically, a window from day 250 to day 30 relative to the event date is chosen (somewhat randomly) in studies employing daily data. However, this mechanical option does come with challenges. Specifically, unrelated events may occur during the selected estimation window, thereby skewing the estimation of the return-generating process parameters. The reader should keep this in mind when interpreting the results from the event study. Moreover, this study chose the 71-day estimation period because we used an event study tool provided by Datastream which is only able to extract and estimate data per 1,000 observations. In other words, for this study, the event study tool was run numerous times to extract and estimate all the data for the market model, since there are around 15,765 observations within the dataset for the event study. In addition, extending the estimation period would result in longer calculation time for the event study tool per 1,000 observations. Since we had to repeat the process of extracting and estimating the data for the market model multiple times, we found it to be sufficient to use an estimation period of 71 days as this is also in accordance with previous literature.

The next step is to define the abnormal returns. The single factor model assumes that a stocks' return is modelled by a systematic factor, related to a market index, and an unsystematic factor, unrelated to the market index. The unsystematic factor is also known as the abnormal return (Coutts, Mills, & Roberts, 1994). The abnormal returns are estimated as following:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) , t = 0,1,2,\dots,T$$

Where α_i and β_i are OLS regression estimations of the parameters for stock (i) estimated over the estimation windows. R_{it} and R_{mt} are respectively return for stock (i) and market returns for period (t).

The Cumulative Abnormal Return (CAR) method uses the abnormal returns during a given event window. It is essential to sum the estimated abnormal returns to find the performance of stocks during the event window. For instance, the abnormal returns of 4 days are cumulated when using an event window of [0; 3]. Subsequently the CAAR is estimated by averaging the CAR. The CAR and CAAR are estimated as following:

$$CAR(t_1; t_2) = \sum_{t_1}^{t_2} AR_i \ ; \ CAAR(t_1; t_2) = \frac{1}{N} \sum_{t_1}^{t_2} CAR_{it}$$

Where AR_i is equal to the abnormal returns of stock (i) and are summed in the time window $[t_1; t_2]$, and N is the number of stocks in the sample.

For the assumption of economic relevance, it is necessary to test whether the abnormal returns are statistically significant. Academic literature suggests two types of tests, namely a parametric and a non-parametric test. For the relevance of this event study a non-parametric test is adopted, as this method is not bound to the assumption of the distribution of returns, hence, does not lack performance when the returns are not considered normal. Proposed by Wilcoxon (1992), the signed-rank test, which is used to test statistical significance of the average abnormal returns (AAR), considers both the signs as well as the magnitudes. In addition, we use the Wilcoxon sign rank test to evaluate to statistical significance of the CAR throughout the various event windows.

4.2. Time series multi-factor model approach: Effect of short selling disclosures

To further enhance the relevance of this study, we evaluate the performance of the shorted stocks in the sample by using a multi-factor model analysis described by Fama and French (1992), next to event study in the previous subsection. In this subsection we provide a second method to test for robustness Thereby, we test the first hypothesis:

H1: European short selling disclosures have a negative impact on stock returns (in the short run)

In the research provided by Fama and French (1992) they found that small-cap stocks outperformed large-cap stocks (SMB), as well as the fact that growth stocks underperform to value stocks (HML). To achieve feeling among these factors we can describe the construction of the SMB factor as following:

$$R^{SMB} = R^{small} - R^{big}$$

In general the SMB and HML factors are seen as an extension to the CAPM-model. Fama and French (1992) define value stocks by using the price-to-book ratio of a stock (a high price-to-book ratio is considered a growth stock) and firm size is defined by its market capitalization. One of the benefits of using factor models is that they eliminate the need to consider cross-sectional and serial correlations as potential issues.

In this analysis, we follow the multi-factor models approach adopted by Jank & Smajlbegovic (2017), which is used to analyze the performance of portfolios. Using this method it is possible to analyze the performance of equal-weighted (EW) and short-value-weighted (SWV) portfolios. Given the fact that the sample comprises solely of individual stocks, the analysis is limited to net shorted positions at entry dates. Therefore, the portfolios are constructed at entry-date and held for 30 more days, consistent with the longest event window applied in the event study in the previous subsection. This implies that Jensen's Alpha is calculated over a 31-day period.

In his approach three models are used, namely the three-factor model (3F), the Carhart four-factor model (4F), and the AQR five-factor model (5F).

The Carhart model adds the momentum factor (UMD). The rationale behind this factor is that investors want a stock that is expected to continue to perform well in the future or, in the case of short sellers, a stock which is expected to continue to do worse in the future when opening a position. Carhart (1997) examines whether persistence in performance can be explained by common factors in stock returns and identifies a significant correlation between performance persistence and stock returns. The three-factor model explains returns better than the CAPM, while the four-factor model explains returns better than the three-factor model, according to Carhart (1997).

The five-factor model adds the betting-against-beta factor (BAB), which was found by Frazzini and Pederson (2014). This model is based on the premise that many investors, including retail and institutional investors, are constrained by their leverage function. In their paper, they argue that investors who are constrained prone to overweigh riskier assets. This behavior appears to suggest that stocks with a high beta require lower risk-adjusted returns compared to stocks with a lower beta.

After the formation of the equal-weighted and short-value-weighted portfolios, a regression on abnormal returns for each portfolio (i) is performed.

$$-(R_{it} - Rf_t) = \alpha_{it} + \boldsymbol{x}_{\boldsymbol{t}}' B_i + \epsilon_{it}$$

Where $R_{it} - Rf_t$ is the return of stock (i) minus the one-month T-bill, and $\boldsymbol{x}_{\boldsymbol{t}}'$ is the vector of all factors included in the model. The stocks that are analyzed are shorted, hence, $R_{it} - Rf_t$ is multiplied by -1. According to Jank & Smajlbegovic (2017), the SMB factor considers that small firms outperform large firms, while the HML factor adjust for the value risk to explain differences in portfolio returns. The size premium entails that firms with a high market capitalization have lower returns as opposed to firms with low market capitalization. The value premium effect encompasses the outperformance of firms with a low book-to-market (B/M) ratio by firms with a high B/M ratio. We add a momentum factor (UMD) which is suggested to be priced in Europe (Carhart, 1997). Moreover, we add the BAB-factor which suggests that risky assets are overpriced, while lower beta stocks are underpriced (Frazzini & Pedersen, 2014). The intercept, α_{it}, represents Jensen's Alpha and explains the abnormal performance of the stock (i) at time (t) after controlling for the factors (MKT, SMB, HML, UMD, BAB). Jensen's alpha from the factor models discloses the magnitude of the performance that cannot be explained by the three, four or five factors (Pan, 2016). In general a non-zero alpha means an exploitable opportunity, but it depends on the sign of the alpha whether one needs to go short. Academics and investors interpret a positive alpha as evidence that a certain skill or additional risk is not captured by the factor model. A statistically significant negative alpha, on the other hand, may imply that the investment portfolio underperforms. As our portfolios only consist of shorted stocks (and the dependent variable is multiplied by -1), a positive alpha would mean that you need to short the entire portfolio to reap the profits.

With the Breusch-Pagan test / Cook-Weisberg test, we test for heteroskedastic standard errors when constructing regression analyses. Assuming homoscedasticity when heteroscedasticity is present, this may result in unbiased, although inefficient, coefficients and biased standard errors. If heteroscedasticity is observed, robust standard errors, also known as the Newey West standard errors, which account for heteroskedasticity in residual distribution, must be employed. (Newey & West, 1987). Hence, in the multi-factor model we use robust standard errors.

4.3. Difference-in-Difference (DID) specification: Effect on liquidity and volatility

In this section we will analyze the effects of the short selling bans on liquidity and volatility in 2020 across multiple European countries. This will help us with respect to testing the second and third hypothesis:

H2: The European short selling bans in 2020 have a negative effect on liquidity

H3: The European short selling bans in 2020 have negative effect on volatility

To investigate the effects of the short selling bans on liquidity and volatility, we use a Difference-in-Difference (DiD) method following recent studies (AFM, 2022; Siciliano & Ventoruzzo, 2020). The DiD approach measures the effect of a certain event when there is one group exposed to this event, whereas the other group is not. These two groups are also known as the treatment group and the control group. As the raw sample consists of pre- and post-ban data, it is possible to examine the causal interference. In other words, the model takes the difference in the treatments pre- and post-ban outcome, also known as the first-difference. Subsequently it takes the difference in the pre- and post-ban outcome of the control group, also known as the second-difference. Taking the difference in the control groups' outcome essentially captures the time-varying effects. The model then discards all time-varying effects, by subtracting the second-difference from the first-difference. This method, also known as the DID estimator, can be formulated as following:

$$\delta = (\bar{y}_{11} - \bar{y}_{12}) - (\bar{y}_{21} - \bar{y}_{22})$$

Where δ is equal to the DID estimator and the $(\bar{y}_{11} - \bar{y}_{12})$ is equal to the change in outcomes before and after the treatment to the control group, while $(\bar{y}_{21} - \bar{y}_{22})$ is equal to the change in outcomes before and after the treatment for the treatment group. That is, the DiD estimator shows the changes in outcomes from pre-ban to post-ban and changes in outcome between the control- and treatment group. One of the main critical assumptions to ensure internal validity in the DiD models is the parallel trend assumption. The parallel trends assumption argues that, prior to the intervention, the outcome trends of the treated and comparison groups are equivalent. If true, it is justifiable to infer that these parallel trends would persist for both groups even if the event (the ban on short sales) were not implemented. This is demonstrated empirically by examining the trends in both categories prior to the implementation of the policy. In principle there is no formal test on the parallel trend assumption, although many academics provide a visual inspection of the pre-treatment trends for the control and treatment group. Hence, we follow previous research and provide visual aid on the parallel trend assumption in figure X. Based on figure 4 we are not able to reject the parallel trend assumption for all dependent variables. Even so, we seek to support the graphs by providing a two-sample t-test for all dependent variables. The reader should, however, be cautious when interpreting the two-sample t-tests as this is not an official way to test parallel trends. The two-sample t-tests are provided in Table 9 and shows that only for the bid-ask spread there is a significant difference between the mean values. For this study we follow the graphs, which show parallel trends. In addition we test whether we can observe heteroskedasticity in the error terms. When there is any trend or pattern in the residual vs. fitted graphs in Figure 5 in the Appendix, provided in figure 4, this could be an indication for heteroskedasticity. Initially we suspected heteroskedasticity of the volatility variables, thus, we have winsorized these variables. These winsorized volatility variables are used as a robustness check in the results section for the analysis on the effects of short sale bans on volatility. In the regressions we also account for heteroskedastic values by using clustered standard errors.

The DiD method is highly relevant for the study, as the effects of short selling are typically examined during periods of restrictions. In the sample, the stocks that are exempted from short selling during the period of 17 March 2020 to 18 May 2020 are considered the treatment group. These stocks are originated from countries who imposes the short selling ban. The control group consist of stocks that are originated from countries who did not impose a short selling ban.

One must understand that for studies on short selling bans and market quality, such as liquidity and volatility, it is difficult to conclude causality from the results. It is not possible to entirely exclude concerns regarding estimates caused by endogeneity of short selling bans. For instance this could happen when financial regulators implement short selling bans in response to declining market quality for various other reasons (Bessler & Vendrasco, 2021). To mitigate potential endogeneity, this study follows other academic studies by using a matching technique (AFM, 2022; Siciliano & Ventoruzzo, 2020). The banned stocks from France, Belgium, and Italy are matched to unbanned stocks from the other EU member countries. The samples of stocks are matched with respect to firm size (average market capitalization in 2019) and by industries, based on the four-digit SIC codes. Using the Coarsened

Exact Matching (CEM) approach helps to provide more robust results. CEM is a non-parametric matching method, which bounds the degree of dependence in a model and estimation errors in causalities, chosen by ex-ante users. Other examples of benefits of the method are the robustness to measurement error, as well as being monotonic imbalance bounding (Blackwell, Iacus, King, & Porro, 2009). Hence, the model can establish balanced covariance between the treatment and control group, while also easing the effect of confounded causal interference. Based on this and the use of the method by other prominent papers on short selling bans, this method is considered most plausible for the research in comparison to other methods such as the Propensity Score Matching (PSM). The Difference-in-Difference model aims to capture the effect of a ban (no-ban) on the dependent variables that are of interest in this study. Similar to the recent studies, the Difference-in-Difference model is as following:

$$MQ_{i,t} = \alpha + \beta_1 During_t + \beta_2 Post_t + \beta_3 During_t \times Ban_{i,t} + \beta_4 Post_t \times Ban_{i,t} + \beta_5 \times Ban_{i,t} + firm\,fixed\,effects + R_{i,t-1} + VSTOXX_{i,t-1} + B/M_{i,t} + Stringency_{i,t} + \varepsilon_{i,t}$$

Where MQ_{it} is a vector of the measures: (1) quoted bid-ask spread, (2) Amihud liquidity (3) Vol5, and (4) Garman and Klass Vol. The Ban variable equals 1 if stock (i) was exposed to a ban during the ban period, and 0 if not. This variable will only provide a coefficient in the Random Effects models due to the fact that it is a time-invariant variable, thus, it will be omitted in the Fixed Effects models (Williams, 2015). The time invariant effects are perfectly collinear with Fixed Effects. $During$, and $Post$ are dummy variables. Firm Fixed Effects are analyst coverage, D/E ratio, and Return on Assets (ROA). The control variables are the lagged return of stock (i) ($R_{i,\ t-1}$) and Euro Stoxx 50 volatility index ($VSTOXX_{i,\ t-1}$), the natural logarithm of B/M, and stringency. The reference period for the model is the pre-ban period. The set of control variables are added to specifications of the model. First, we add book-to-market and the lagged return of one-day. At a country level we follow Siciliano & Ventoruzzo (2020) by adding stringency, which is extracted from The Oxford Covid-19 Government Response Tracker. Controlling at European level we follow European Securities and Markets Authority (2022) by adding the lagged return of VSTOXX. In addition, we follow Beber & Pagano (2013) by adding stock level Fixed Effects, such as analyst coverage, as well as adding return on assets (ROA), and leverage (debt-to-equity ratio).

Other studies have demonstrated the effectiveness of using a DiD model to analyze the 2008 financial crisis. Beber & Pagano (2013) provide a DiD model in which the restricted financial stocks are the treatment group and the non-financial stocks are the control group. Intriguingly, the results indicate a reversal of effects when financial stock restrictions are lifted. When bans are introduced or rescinded, they appear to have similar magnitude effects in the opposite direction.

5. Results

Besides the use of descriptive statistics and figures, the regression models in the results section of this paper concisely illustrate the study's findings. The objective is to give findings that ought to include a thorough explanation of the data, statistical measures, and the statistical significance and effect corresponding to those measures. The empirical results of each hypothesis are discussed. The first subsection offers evidence regarding the performance of disclosed net short positions within the timeframe 1 November 2012 to 31 August 2022. In addition, the effects of short selling bans on liquidity and volatility in France, Italy and Belgium between 17 March 2020 and 18 May 2020 will be discussed and evaluated in the second and third subsections.

5.1. Stock performance results

For the analysis of stock performance we provide results of the market model containing Cumulative Abnormal Returns across different event windows. For robust results, this paper provides a second analysis using factor models in which two kinds of portfolios are formed.

5.1.1. Market Model results

In this subsection we will provide results with regards to the event study to either reject or accept the following hypothesis:

H1: European short selling disclosures have a negative impact on stock returns (in the short run)

Figure 3 depicts the Average Abnormal Returns (AAR) on a daily basis over the entire sample of disclosed net short positions. Interestingly, this demonstrates that the AAR continue to be negative until three days after the net short position is disclosed. This means that short sellers, on average, continue to enjoy abnormal returns until this period. In addition, Figure 3 demonstrates that the average abnormal returns continue to be positive in a fairly consistent manner after day three. It is important to keep in mind that the event day is the day where a net short position is disclosed to the relevant financial authority. This would indicate that on the long term, in our study, the performance of the disclosed net shorted positions is decreasing. As a result, events such as subsequent short positions and exits are not taken into consideration in either this graph or the results that are presented below regarding the Cumulative Abnormal Returns.

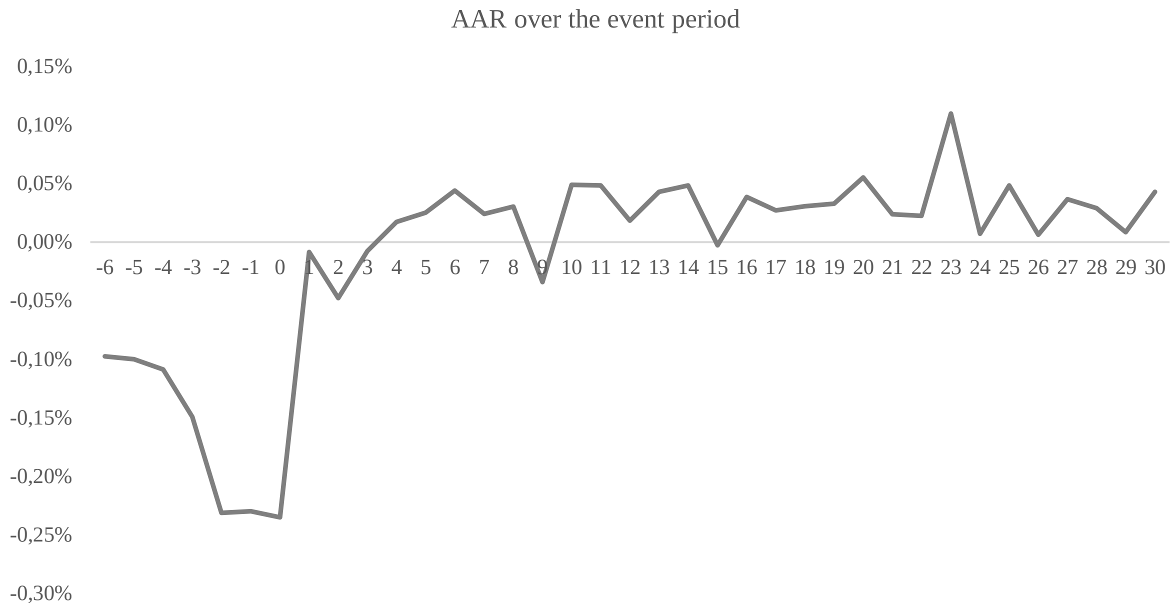

Figure 3: the average abnormal returns over a 37 day-period within the sample period

To investigate on a stock-by-stock basis, we would like to offer the Cumulative Abnormal Returns (CAR), as mentioned in the previous section. The research provides a market model in which different event windows are used pre-event and post event. We show different event-windows to show consistency across the different windows, as well as statistical significance. Table 11 shows the Cumulative Abnormal Returns and their statistical significance. Statistical significance is provided by t-tests and the Wilcoxon sign rank test.

Table 11: CARS of net short positions disclosures for various event windows

	Mean	SE	Wilcoxon Sign Rank Test (Z)
CAR [-6; -1]	-0.897%***	-0,0006	-14,190***
	(-15,354)		
CAR [-5; -1]	-0.797%***	-0,0005	-13,718***
	(-14,991)		
CAR [-4; -1]	-0.707%***	-0,0005	-13,838***
	(-14,88)		
CAR [-3; -1]	-0.596%***	-0,0004	-13,449***
	(-14,626)		
CAR [-2; -1]	-0.447%***	-0,0003	-12,909***
	(-13,459)		
CAR [0;1]	-0.250%***	-0,0003	-6,730***
	(-7,282)		
CAR [0;2]	-0.290%***	-0,0004	-6,321***
	(-7,144)		
CAR [0;3]	-0.299%***	-0,0005	-5,550***
	(-6,476)		
CAR [0;4]	-0.269%***	-0,0005	-4,851***
	(-5,303)		
CAR [0;5]	-0.234%***	-0,0006	-3,920***
	(-4,234)		
CAR [0;10]	-0.136%*	-0,0007	-1,334
	(-1,841)		
CAR [0;20]	0.265%***	-0,001	2,905***
	(2,586)		
CAR [0;30]	0.661%***	0,001	5,578***
	(5,091)		

Notes. This table documents the Cumulative Abnormal Returns (CAR) for different event windows using the market model. CAR is calculated by cumulating the daily abnormal return within the event window. The T statistics are given in parentheses, and *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively

The findings of the market model's estimation of the Cumulative Abnormal Returns are presented in Table 11, together with the statistical significance of those estimates. The model is applied in order to analyze the performance of disclosed shorted stocks throughout a variety of event windows. In the event windows prior to the event we are able to test the performance of stocks before they disclosed to the relevant competent authority. In general, these event windows may suggest possible information leakage or insider trading (Senchack & Starks, 1993). The coefficients of the pre-event windows vary between -0.897% through -0.447%, implying that as the event-window length decreases, the CAR correspondingly declines. Considering we find negative CARs during the pre-event windows; this could signal that there is information leakage or insider trading shortly before the event. Also, all coefficients are statistically and economically significant. The post-event windows may test the speed of information implementation. According to the results of Table 11, it appears that for all the event windows until 10 days are negative and vary between -0.299% [0;3] and -0.136% [0;10]. It seems that when the post event-window is 20 or 30 days the coefficients become positive. Almost all coefficients seem to be economically and statistically significant. The study only indicates statistically negligible Cumulative Abnormal Returns, based on the Wilcoxon Sign Rank test, inside the 11-day event window [0;10], while it yields statistically significant and positive Cumulative Abnormal Returns over the 21-day span [0;20] and [0;30]. Considering that all post-event periods give consistent and decreasing negative coefficients, one might argue that disclosures of short sales have little impact on the Cumulative Abnormal Returns. When comparing the negative coefficients of the pre-event windows with the negative coefficients of the post-event windows, we notice that the pre-event coefficients are considerably more negative. When taken as a whole, it still would appear that the findings lend credence to the idea that short sellers are informed traders, as was proposed in previous studies. This is because in all event windows, except for the two longest windows, they are able to reap the benefits of shorting a stock. Hence, based on this event study model we cannot reject the hypothesis that European short selling disclosures have a negative impact on stocks returns, since the negative abnormal returns still exist after the event of disclosure has occurred. Nonetheless, the results provide evidence on the fact that in a longer time window these benefits may not exist anymore. In order to find robust results regarding the performance of disclosed net short positions, we provide a multi-factor model for which the findings are presented in the next subsection.

5.1.2.Multi-factor model results

This subsection will provide an analysis in support of the previous subsection, discussing the market model, where results are provided with the use of short selling portfolios by analyzing the Jensen's alpha of various factor models. These results are given to either reject or accept the following hypothesis:

H1: European short selling disclosures have a negative impact on stock returns (in the short run)

The role of alpha is of great importance within this section. The reader must consider that a non-zero alpha means that there is an exploitable opportunity for investors, meaning that there are returns without risk. In addition, the alpha presents the performance of the equally-weighted portfolio (EW) and short-value-weighted (SVW) portfolio. Table 12 presents the results on the performance of short sales using various factor models.

Table 12: the performance of short sales using factor models

	(1)	(2)	(3)	(4)	(5)	(6)
	EW	EW	EW	SVW	SVW	SVW
MKTRF	-2.042***	-2.149***	-2.063***	-2.221***	-2.421***	-2.317***
	(0.595)	(0.640)	(0.665)	(0.574)	(0.661)	(0.711)
SMB	-3.614**	-3.371**	-3.902**	-2.577*	-2.123	-2.770
	(1.434)	(1.493)	(1.691)	(1.298)	(1.387)	(1.845)
HML	-2.189	-2.682	-2.051	-2.778	-3.697	-2.929
	(1.395)	(1.596)	(1.706)	(2.205)	(2.564)	(2.600)
UMD		-0.943	-0.544		-1.759	-1.272
		(1.104)	(1.339)		(1.521)	(1.689)
BAB			0.667			0.813
			(0.656)			(1.146)
α	0.0552*	0.102	0.0519	0.0809***	0.168*	0.107
	(0.0269)	(0.0657)	(0.0947)	(0.0264)	(0.0885)	(0.122)
R^2	0.642	0.649	0.656	0.474	0.491	0.499
Adjusted R^2	0.602	0.595	0.587	0.416	0.413	0.399

Notes. This table provides results on the performance of short sales. We form two portfolios: equally-weighted (EW) portfolios and short-value-weighted (SVW) portfolios to capture the abnormal returns. Portfolios are formed at each event-day and are held for 31 days. The portfolio returns are regressed on market excess returns factor (MKTRF), small-minus-big factor (SMB), high-minus-low factor (HML), momentum factor (UMD), and betting-against-beta factor (BAB). The table reports robust standard errors in parentheses. For the market beta it is hypothesized that equals -1, instead on 1, because this are short selling portfolios. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

When evaluating the adjusted R - squared value of both the portfolios, we encounter that the equally-weighted portfolios outperform the short-value-weighted portfolios throughout all factor models and increases when adding variables. The adjusted R - squared of the models informs how well the independent variables explain the abnormal returns of the portfolios, thus, the three-factor models explain the proportion of variation best. The adjusted R - squared for equally-weighted portfolios vary between 0.587 and 0.602, whereas it ranges between 0.399 and 0.416 for the short-value-weighted portfolios. One should keep in mind that this analysis is on portfolios which are formed at event dates and are held for one month, which implies they include all shorted stocks that are revealed on a specific date. This does not identically resemble the investment strategies provided by Jank & Smajlbegovic (2017), yet it continues to yield interesting results. Moreover, the model is multiplied by -1 since we use short positions, following Jank and Smajlbegovic (2017). Initially, we discover that the MKTRF is negative with a value below -1, implying that the short portfolio encompasses speculative and risky stocks. A coefficient of -2.042 in the three-factor model for an equally-weighted portfolio indicates that with every 1% rise in MKTRF, the overall portfolio abnormal return is anticipated to go down by 2.042%. Across all models and portfolios, the MKTRF coefficients are statistically significant at a 1%-level and consistently negative. Furthermore, the analysis shows that short sellers disclose net short positions in large-cap stocks. For all three models, the negative coefficients for SMB are statistically significant at a 5%-level for equally weighted portfolios. For further consideration, we would like to emphasize that one should be careful when interpreting the SMB factor for the following reason. First, Kenneth and French have created the SMB factor in way that along the size dimension, stocks are sorted into two categories: small and big. In addition, the SMB factor has been modeled by Kenneth and French by using a coarser double sort method (Pan, 2016). In principle this leads to a SMB factor which is constructed by a long / short strategy. In the course of short selling bans, short selling is prohibited, thus, could make the model inadequate. In other words, the reader should keep mind that this analysis is constructed on a dataset where short selling restrictions are present in 2020 which most certainly affects the SMB factor. Nonetheless, considering the three-factor model, we discover a coefficient of -3.614 which tends to mean that an increase in SMB by 1% results in a decrease of the abnormal return of the portfolio by 3.614%. In particular, this indicates that the excess return is derived from small-cap companies. The factors UMD in the four-factor model and BAB in the five-factor model have no statistical significance. Looking at Jensen's alpha, we find that the three-factor model achieves an alpha of 0.05% at a significance level of 10%, whilst the short-value-weighted portfolio achieves statistical significance at 1% and 10% for the three- and four-factor models, respectively. The table illustrates an alpha of 0.08% for the three-factor model over a 31-day timespan. Besides, the four-factor model shows an alpha of 0.17% for the short-value-weighted model. The findings of the models indicate that the performance of short sales is positive, although adding more factors to the model seems to decrease the level of significance of the alpha. Nonetheless, the findings are consistent with the Cumulative Abnormal Returns that were reported in the event study in the previous subsection. The outcomes of the models support the theory that short sellers are informed traders and are able to exploit unexplainable excess returns. Hence, creating an investment strategy which follows net short position disclosures can be lucrative, although, the reader should keep in mind that these abnormal returns derived from the factor models are quite small.

5.2. Difference-in-Difference specification: Results on liquidity

In this subsection the results for the effects of short selling bans on liquidity are presented and discussed. The liquidity measures are the dependent measures and within the Difference-in-Difference model, this paper uses the pre-ban period as reference period. Thus, liquidity during and post the short selling ban are analyzed. Table 13 presents estimates of regressions in which the dependent variable is the natural logarithm of the Amihud liquidity measure, while Table 14 documents the estimates of regressions on the square root of the quoted bid-ask spread. More specifically, columns (1) and (2) provide Fixed Effects (FE) models, whereas columns (3), (4), and (5) provide Random Effects (RE) models. The FE model assumes that the effect of an independent variable is constant across all observations, whereas RE model assumes presumes that the independent variable's effect can differ across observations. A Hausmann test is also provided to examine which model is best fit. The test's null assumption is that the Random Effects model is preferred because it is more efficient. It is essential to understand whether the unobserved individual-specific effects are correlated with other explanatory variables when deciding between models (Hausman & Taylor, 1981). If these are correlated, the FE model appears to provide a better fit since it takes these effects into account. Despite small coefficient differences, the FE model is better for both liquidity measurements. The study interprets columns (1) and (2) for both liquidity measures. We check compatibility and consistency by use of the RE models in columns (3), (4) and (5).

Table 13: Panel regression - the effect of short selling bans in France, Italy and Belgium on the Amihud liquidity

	(1)	(2)	(3)	(4)	(5)
	Amihud Liquidity	Amihud Liquidity	Amihud Liquidity	Amihud Liquidity	Amihud Liquidity
During	-0.578***	-0.005	-0.578***	-0.010	-0.014
	(0.0237)	(0.030)	(0.024)	(0.0299)	(0.030)
Post	-0.220***	0.108***	-0.220***	0.110***	0.108***
	(0.0266)	(0.030)	(0.027)	(0.030)	(0.031)
During × Ban	-0.136***	-0.118***	-0.136***	-0.118***	-0.118***
	(0.0344)	(0.033)	(0.034)	(0.032)	(0.033)
Post × Ban	-0.104***	-0.072**	-0.104***	-0.076**	-0.078**
	(0.0378)	(0.035)	(0.038)	(0.035)	(0.035)
Ban			-0.095	0.262	-0.755
			(0.179)	(0.193)	(1.232)
$R_{i, t-1}$		0.640***		0.673***	0.647***
		(0.110)		(0.109)	(0.109)
B/M		-1.390***		-1.332***	-1.326***
		(0.058)		(0.055)	(0.051)
Stringency		-0.004***		-0.004***	-0.004***
		(0.000)		(0.000)	(0.000)
$VSTOXX_{i, t-1}$		0.426***		0.425***	0.422***
		(0.036)		(0.036)	(0.036)
Analyst coverage					1.029***
					(0.256)
D/E					0.246***
					(0.067)
ROA					0.036
					(0.008)
Intercept	18.440***	17.550***	18.341***	17.324***	16.871***
	(0.011)	(0.044)	(0.119)	(0.146)	(1.260)
Firm FE	Yes	Yes	No	No	No
Country controlled	No	No	No	No	Yes
Observations	110,973	103,665	110,973	103,665	101,829
R-squared	0.052	0.093	0.052	0.093	0.093
Adjusted R-squared	0.052	0.093			
Between R-squared	0.001	0.010	0.001	0.009	0.189
Number of firms	930	876	930	876	859

Notes. This table shows the effect of explanatory variables on the Amihud liquidity. Models (1) and (2) are Fixed Effects models, while models (3), (4) and (5) are Random Effects models. $R_{i, t-1}$ is a control variable which stands for the one-day lagged return of stock (i). B/M is the natural logarithmic value of the book-to-market ratio. Stringency is the a composite measure constructed with the use of nine response indicators, as explained in the data section on control variables. The measure is scaled between a value of 0 to 100, with 100 being most stringent. $VSTOXX_{i, t-1}$ is the lagged return of the Euro Stoxx 50 volatility index. Analyst coverage is a dummy variable that equals one when a stock is covered and zero when a stock is not covered. The D/E is the debt-to-equity ratio and the ROA is the return on assets. The clustered standard errors are presented in the parentheses and statistical significance is presented as *** p<0.01, ** p<0.05, * p<0.1.

Table 13 documents the results on the liquidity measures throughout different models. Column (1) shows that the Amihud liquidity coefficient is -0.578 during the ban period. This implies that during the ban period, all stocks from the matched sample seem to have a lower liquidity compared to the reference period of January 17th to March 17th, 2020. The primary focus, however, lies on the interaction variable of during and ban, as this variable is the DiD estimator. It indicates whether the expected mean change in outcome was the same or different between the treatment and control groups before and during the ban. To interpret this coefficient, the reader should remember that the null hypothesis of this measure stipulates that there is no difference between the treatment and control groups and that nothing has changed between the pre- and during periods. In addition, one should look at $\beta 1 + \beta 3$ (beta's for During and During $\times$ Ban) to get the estimated mean difference in the dependent variable. As a result, when the interaction variable (During $\times$ Ban) is considered, the effect is stronger (-0.578 - 0.136 = -0.714). When the post period is compared to the pre-period, the results from column (1) have a negative impact on the Amihud liquidity measure (-0.220). Furthermore, when the interaction variable is taken into account, the effect becomes stronger (-0.324). The control variables are then added to the model in column (2). We find that liquidity is lower during the ban period, though the effect is much smaller (-0.005) than in the baseline model. The interaction variable indicates that the banned stocks have a greater negative impact on the Amihud liquidity measure during the ban period. For both models we find that the interaction variables are statistically significant at an 1%-level. In addition, we find that all control variables are also statistically significant. For consistency, we find that the results in columns (3) through (5) are consistent with the first two models.

For the Fixed Effects model we look at the adjusted R-squared since a normal R-squared will tend to increase when including more explanatory variables. The adjusted R-squared allows us to compare the goodness-of-fit for the Fixed Effects models, which vary in the number of explanatory variables, in column (1) and column (2) of Table 13. Interestingly, the adjusted R-squared is almost equal to the R-squared. The difference may only be observed in decimals, although we round to three decimals. The second model has the highest adjusted R-squared value, which indicates that the proportion of variance that can be attributed to the independent variables is better described by this model. Next, for the interpretation of the Random Effects model, we look at the between R-squared, rather than the adjusted R-squared. The between R-squared measures the proportion of variation between the panel units which the Random Effects model account for. The between R-squared is highest for the third Random Effects model, thus this model best explains the proportion of variation between the panel units. The reader must understand that we do not compare the R-squared of the Random Effects model with that of the Fixed Effects model as this is invalid. One can only compare the R-squared between the same models. Moreover, we find that the observations and number of firms differ between the models, which is caused by the fact that for certain explanatory variables we have missing data for certain days which is explained in the data section. Moreover, Fixed Effects models are based on panel data, which involves observations across multiple firms over time. The reader can see that throughout the models, when adding more independent variables, this decreases the number of observations. For instance, adding the lagged returns would obviously decrease the number of observations, because we miss data on the second day of the time-period for every firm. In addition, we do not have B/M and D/E data for every firm, thus this decreases the number of firms.

Next, we show the results on the quoted bid-ask spread in Table 14, in which column (1) and (2) are interpreted for this study as these models are best fit according to the Hausman test. The coefficients in Table 14 are presented as percentages, since the coefficients are rather small. Column (1) documents the effect of the ban period on the quoted bid-ask spread. Column (1) shows that the quoted bid-ask spread coefficient is 0.598% during the ban period. Moreover, we find that the effects are stronger for the banned stocks during this period (0.906%), meaning that for the banned stocks in France, Italy and Belgium, the quoted bid-ask spread is higher. This in fact means that the spread is wider, hence, the stocks are more illiquid. When adding control variables, as presented in column (2) the results indicate that during the ban period the quoted bid-ask spread is tighter for the full sample, although when considering the interaction variable (During × Ban), the effect of the ban has a tightening effect (-0.202% + 0.286% = 0.084%). This in fact means that the effect of a ban has a negative effect on the liquidity of the banned stocks. In other words, the model shows that liquidity is higher during the ban period for the full matched sample in column (2), whilst lower for the banned stocks during this period. Considering the results of both specifications, it seems that both models support the fact that liquidity is lower for the banned stocks within the ban period, compared to the reference period. For more robust results, we find that the results in columns (3)-(5) support this idea.

Moreover, column (2) in Table 14 shows that when the ban is lifted the quoted bid-ask spread becomes tighter (-0.339) for the full sample. This means that the stocks during the post period seem to be more illiquid, with 17th of January 2020 to 17th of March 2020 as the reference period. Furthermore, the DiD estimator in the post-period (interaction variable of Post × Ban) is equal to 0.097% in column (2), thus, having a widening effect on the quoted bid-ask spread. With these results in mind it appears that the expected mean change in the quoted bid-ask spread is higher post-period referenced to the pre-ban period. Also, the results imply that almost all explanatory variables are statistically significant throughout the models, except the one-day lagged return of a stock. Finally, the second Fixed Effects model has the greatest adjusted R-squared (0.063), which indicates that the second model is better at describing the proportion of variance that can be assigned to the independent variables.

With regards to the second hypothesis which states that the effect of short selling bans has a negative effect on liquidity, we find that during the ban period all stocks seemed to suffer from a decrease in liquidity based on the Amihud liquidity measure. Moreover, we find that for banned stocks this effect is even more negative, based on the interaction variable in Table 13. This is in line with expectations and previous literature (AFM, 2022; Boehmer, Jones, & Zhang, 2013; Siciliano & Ventoruzzo, 2020).

In addition, we find robust results based on the quoted bid-ask spread in Table 14. The model shows that based on the During × Ban variables, banned stocks from France, Italy, and Belgium appear to have wider quoted bid-ask spreads, indicating that they are less liquid. Based on these results we are not able to reject the second hypothesis.

Table 14: Panel regression - the effect of short selling bans in France, Italy and Belgium on the quoted bid-ask spread

	(1)	(2)	(3)	(4)	(5)
	Quoted bid-ask spread	Quoted bid-ask spread	Quoted bid-ask spread	Quoted bid-ask spread	Quoted bid-ask spread
During	0.598***	-0.202***	0.598***	-0.189***	-0.199***
	(0.034)	(0.049)	(0.034)	(0.049)	(0.0495)
Post	0.213***	-0.339***	0.213***	-0.345***	-0.355***
	(0.034)	(0.047)	(0.034)	(0.047)	(0.047)
During × Ban	0.308***	0.286***	0.308***	0.285***	0.289***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Post × Ban	0.057	0.097**	0.057	0.107**	0.110**
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Ban			0.500***	0.228	0.156
			(0.137)	(0.150)	(0.917)
$R_{i, t-1}$		-0.184		-0.271*	-0.280*
		(0.165)		(0.165)	(0.167)
B/M		1.220***		1.060***	1.060***
		(0.081)		(0.071)	(0.0708)
Stringency		0.008***		0.009***	0.007***
		(0.000)		(0.001)	(0.001)
$VSTOXX_{i, t-1}$		0.272***		0.274***	0.269***
		(0.049)		(0.049)	(0.049)
Analyst coverage					-0.757***
					(0.211)
D/E					-0.184***
					(0.059)
ROA					-0.0293***
					(-0.007)
Intercept	3.350***	3.990***	3.110***	3.780***	4.911***
	(0.0138)	(0.0579)	(0.0960)	(0.136)	(1.260)
Firm FE	Yes	Yes	No	No	No
Country controlled	No	No	No	No	Yes
Observations	117,781	108,995	117,781	108,995	106,890
R-squared	0.041	0.063	0.041	0.063	0.093
Adjusted R-squared	0.041	0.063			
Between R-squared	0.020	0.006	0.020	0.009	0.102
Number of firms	930	876	930	876	859

Notes. Notes. This table shows the effect of explanatory variables on the quoted bid-ask spread. Models (1) and (2) are Fixed Effects models, while models (3), (4) and (5) are Random Effects models. $R_{i, t-1}$ is a control variable which stands for the one-day lagged return of stock (i). B/M is the natural logarithmic value of the book-to-market ratio. Stringency is the a composite measure constructed with the use of nine response indicators, as explained in the data section on control variables. The measure is scaled between a value of 0 to 100, with 100 being most stringent. $VSTOXX_{i, t-1}$ is the lagged return of the Euro Stoxx 50 volatility index. Analyst coverage is a dummy variable that equals one when a stock is covered and zero when a stock is not covered. The D/E is the debt-to-equity ratio and the ROA is the return on assets. The coefficients are presented in percentages. The clustered standard errors are presented in the parentheses and statistical significance is presented as *** p<0.01, ** p<0.05, * p<0.1.

5.3. Difference-in-Difference specification: Results on volatility

This subsection exhibits and discusses the short selling ban impact on volatility. The volatility measures are the dependent variables in the Difference-in-Difference models. The regression models use the pre-period, which is January 17th 2020 through March 17th 2020, as reference period. Hence, volatility is evaluated during and after the short selling restriction. Table 15 exhibits the first volatility measure: the 5-day rolling standard deviation of returns using closing prices (Vol5).

Table 15 documents the results on the 5-day rolling standard deviation of returns using closing prices (Vol5) throughout different models. Column (1) shows that the Vol5 coefficient is equal to 0.253 during the ban period. This suggests that for all stocks from both the treatment (ban=1) and control (ban=0) group seem to have a positive effect on volatility during the ban period, referenced to the pre-ban period of the 17th of January 2020 to March 17th 2020. The main focus for this analysis lies on the interaction variable (During × Ban), since this variable is considered the Difference-in-Difference estimator and provides evidence on whether the expected mean change in outcome was different between the banned and unbanned stocks before and during the ban. Particularly, it gives the reader an indication on the effect that the short selling ban had on the volatility of stocks. Column (1) implies a coefficient of the interaction variable (During × Ban) that is equal to -0.077. This means that volatility for all stocks increased statistically significant during the ban period compared to the reference period, since the estimated mean difference in the dependent variable equals to 0.176 (0.256 – 0.077). While for the banned stocks this indicates that volatility decreased significantly during the ban period. In other words, we find that volatility increased during the ban period, although this effect was smaller for the banned stocks. This seems to be in line with the expectations of the results shown by AFM (2022). One could understand that the uncertainty of Covid-19 would increase the volatility of non-banned stocks, while for banned stocks the volatility does not increase, as short sellers are not able to short these stocks.

In contrast, when the control variables are added in column (2) we find that the volatility decreases (-0.119) during the ban period for the full sample, in reference to the pre-period. When considering the banned stocks during the ban period, we find that these have a negative coefficient equal to -0.086. These results indicate that during the short selling ban volatility decreased, whilst for the banned stocks the effect was even stronger (-0.119 -0.086 = -0.205). This actually would imply that a short selling ban during this period was effective, which is contrast with the findings of Beber & Pagano (2013). In addition, column (1) and (2) present independent variables which are statistically significant at a 1%- level, except the interaction variable Post × Ban. For consistency, we find that the coefficients in columns (3) are perfectly consistent with that of column (1), also indicating that the RE model and FE model are very alike. Likewise, we find that columns (4) and (5) are consistent with model (2). Based on the adjusted R-squared we find that the second Fixed Effects model has the highest adjusted R-squared (0.184), which means the proportion of variance that can be attributed to the independent variables is better described by the second model. Considering these quite varying results across the models, we find that the second model is then best model based on the adjusted R-squared. From these results we can say that in comparison towards the reference period, volatility has decreased more for the banned short selling stocks than for the full sample. In other words, the second model shows that stocks in France, Italy and Belgium exhibited lower volatility during the ban period.

Table 15: Panel regression - the effect of short selling bans in France, Italy and Belgium on 5-day (weekly) rolling standard deviation of returns (Vol5)

	(1)	(2)	(3)	(4)	(5)
	Vol5	Vol5	Vol5	Vol5	Vol5
During	0.253***	-0.119***	0.253***	-0.089***	-0.090***
	(0.009)	(0.015)	(0.009)	(0.015)	(0.016)
Post	-0.021***	-0.271***	-0.021***	-0.287***	-0.287***
	(0.007)	(0.012)	(0.007)	(0.012)	(0.012)
During × Ban	-0.077***	-0.086***	-0.077***	-0.088***	-0.087***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)
Post × Ban	-0.015	-0.002	-0.015	0.024**	0.0231**
	(0.010)	(0.013)	(0.010)	(0.011)	(0.011)
Ban			-0.043***	-0.139***	0.005
			(0.012)	(0.019)	(0.077)
$R_{i,\,t-1}$		0.549***		0.344***	0.336***
		(0.085)		(0.091)	(0.093)
B/M		0.565***		0.204***	0.197***
		(0.035)		(0.014)	(0.013)
Stringency		0.004***		0.005***	0.005***
		(0.000)		(0.000)	(0.000)
$VSTOXX_{i,\,t-1}$		0.195***		0.200***	0.198***
		(0.014)		(0.014)	(0.014)
Analyst coverage					0.060**
					(0.024)
D/E					0.009
					(0.006)
ROA					-0.004***
					(0.001)
Intercept	0.425***	0.724***	0.447***	0.536***	0.351***
	(0.004)	(0.027)	(0.008)	(0.016)	(0.078)
Firm FE	Yes	Yes	No	No	No
Country controlled	No	No	No	No	Yes
Observations	114,097	107,269	114,097	107,269	105,195
R-squared	0.091	0.184	0.0911	0.165	0.093
Adjusted R-squared	0.091	0.184			
Between R-squared	0.060	0.006	0.061	0.000	0.012
Number of firms	930	876	930	876	859

Notes. This table shows the effect of explanatory variables on the VOL5, which is the 5-day rolling standard deviation on returns based on closing prices. Models (1) and (2) are Fixed Effects models, while models (3), (4) and (5) are Random Effects models. $R_{i,\,t-1}$ is a control variable which stands for the one-day lagged return of stock (i). B/M is the natural logarithmic value of the book-to-market ratio. Stringency is the a composite measure constructed with the use of nine response indicators, as explained in the data section on control variables. The measure is scaled between a value of 0 to 100, with 100 being most stringent. $VSTOXX_{i,\,t-1}$ is the lagged return of the Euro Stoxx 50 volatility index. Analyst coverage is a dummy variable that equals one when a stock is covered and zero when a stock is not covered. The D/E is the debt-to-equity ratio and the ROA is the return on assets. The clustered standard errors are presented in the parentheses and statistical significance is presented as *** p<0.01, ** p<0.05, * p<0.1.

Next to the Vol5 measure, we show results for the more efficient measure, known as the Garman and Klass volatility (in Table 16 presented as the Garman and Klass Vol). This measure is also a 5-day rolling standard deviation of return, although, this measure uses high, low, opening-, and closing prices. The results for the Garman and Klass volatility measure are presented in Table 16. Column (1) implies that volatility during the ban period increases by 0.241 for the full sample in reference to the pre-ban period. In addition, the Difference-in-Difference estimator in column (1) indicates that the effect of a ban during the ban period has a negative effect on volatility (-0.040), which is statistically significant at a 1%-level. In other words, this means that the coefficient on Garman and Klass volatility becomes negative and different from zero. Particularly, volatility decreases by 0.040 more than it would have without the implementation of the ban for the banned stocks, in comparison to the reference period. This outcome means that volatility for the banned stocks increased statistically significant during the ban period compared to the reference period, since the estimated mean difference in the dependent variable equals to 0.181. Nonetheless, it means that volatility decreased for the banned stocks, thus, meaning the ban was actually effective in that matter. We find consistent results for the Garman and Klass volatility measure to the previous volatility measure (Vol5).

We find that in the first Fixed Effect model (column 1) the Post variable and the interaction variable Post × Ban are not statistically significant, while the During variable and the interaction variable During × Ban are both statistically significant at a 1%-level. In column (2) the only statistically non-significant variable is the Post variable. During and During × Ban are both statistically significant at a 1%-level. Moreover, Table 16 demonstrates that the models (1) and (3) are consistent with each other, while model (4) and (5) are both consistent with model (2).

The adjusted R-squared in the second Fixed Effects model has the highest adjusted R-squared (0.284), meaning the proportion of variance that can be attributed to the independent variables is better described by the second Fixed Effects model. For this reason, we interpret results from column (2) for the third hypothesis. Column (2) indicates that during the ban period, volatility decreased significantly compared to the reference period. In addition, it shows that for the banned stocks volatility was lower (-0.039) during the ban period. Particularly, this outcome means that volatility decreased for the banned stocks, hence, the ban was actually effective in that matter.

With regards to the effect of short selling bans in France, Italy and Belgium on the volatility measures, we find that during the ban period banned stocks had a lower degree of volatility according to the two dependent volatility variables. For the banned stocks we observe that the volatility decreases during the ban period of the 17th of March 2020 until 18th of May 2020. This is in line with the expectations of this paper and with that which is presented in previous papers regarding short selling effects on market quality (AFM, 2022; Siciliano & Ventoruzzo, 2020). Based on these results we are able to reject the third hypothesis, stating that European short selling bans have a negative effect on volatility.

Table 16: Panel regression - the effect of short selling bans in France, Italy and Belgium on Garman and Klass Vol

	(1)	(2)	(3)	(4)	(5)
	Garman and Klass Vol	Garman and Klass Vol	Garman and Klass Vol	Garman and Klass Vol	Garman and Klass Vol
During	0.241***	-0.062***	0.241***	-0.043***	-0.044***
	(0.008)	(0.012)	(0.008)	(0.012)	(0.012)
Post	0.001	-0.194***	0.001	-0.204***	-0.205***
	(0.006)	(0.010)	(0.006)	(0.010)	(0.010)
During × Ban	-0.040***	-0.039***	-0.040***	-0.040***	-0.038***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.009)
Post × Ban	-0.010	-0.002	-0.010	0.015*	0.015*
	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
Ban			-0.055***	-0.152***	-0.057
			(0.011)	(0.021)	(0.114)
$R_{i, t-1}$		0.080*		-0.053	-0.052
		(0.042)		(0.046)	(0.047)
B/M		0.517***		0.286***	0.280***
		(0.030)		(0.016)	(0.016)
Stringency		0.003***		0.0036***	0.004***
		(0.000)		(0.000)	(0.000)
$VSTOXX_{i, t-1}$		0.076***		0.078***	0.079***
		(0.008)		(0.008)	(0.008)
Analyst coverage					0.098***
					(0.030)
D/E					0.004
					(0.008)
Return on assets					-0.004**
					(0.001)
Intercept	0.409***	0.694***	0.436***	0.606***	0.438***
	(0.003)	(0.023)	(0.007)	(0.021)	(0.115)
Firm FE	Yes	Yes	No	No	No
Country controlled	No	No	No	No	Yes
Observations	113,007	106,234	113,007	106,234	104,203
R-squared	0.160	0.285	0.160	0.271	0.093
Adjusted R-squared	0.160	0.284			
Between R-squared	0.0507	0.00947	0.0529	0.00151	0.00275
Number of firms	930	876	930	876	859

Notes. Notes. This table shows the effect of explanatory variables on the Garman and Klass Vol. Models (1) and (2) are Fixed Effects models, while models (3), (4) and (5) are Random Effects models. $R_{i, t-1}$ is a control variable which stands for the one-day lagged return of stock (i). B/M is the natural logarithmic value of the book-to-market ratio. Stringency is the a composite measure constructed with the use of nine response indicators, as explained in the data section on control variables. The measure is scaled between a value of 0 to 100, with 100 being most stringent. $VSTOXX_{i, t-1}$ is the lagged return of the Euro Stoxx 50 volatility index. Analyst coverage is a dummy variable that equals one when a stock is covered and zero when a stock is not covered. The D/E is the debt-to-equity ratio and the ROA is the return on assets. The clustered standard errors are presented in the parentheses and statistical significance is presented as *** p<0.01, ** p<0.05, * p<0.1.

6. Discussion and Conclusion

European regulators were effective in compelling short sellers to increase their level of transparency regarding their holdings. It is without a doubt that many academics find that short selling plays a huge part in stabilizing financial markets, nonetheless, many others have not been too keen about short selling. In this study we aim to provide more knowledge on the concept of short selling by examining and explaining the performance of net short positions within Europe. The research encompasses a unique setting due to the exogenous shock that has impacted financial markets in the course of Covid-19. This pandemic resulted in different reactions by relevant competent authorities of various European countries which we investigated and have provided conclusions in this paper for the reader to examine. In addition to models that are given on this matter, we aim to contribute to the many academic papers that have been written on the matter of the negative effects of short selling bans on market quality. In this paper we provide the reader with an understanding of the negative effect that the short selling bans in 2020 across France, Italy, and Belgium have had on liquidity and volatility. Hence, this study aims to answer the following research question: *What is the effect of short selling disclosures on stock performance, and to what extent do short selling bans impact liquidity and volatility?*

The answer on the research question is provided on the basis of three hypotheses. The first hypothesis states that the European short sale disclosures have a negative impact on stock returns. In other words, it states that the net short positions that are disclosed by the relevant competent authorities impact the stock returns in a negative way, hence, resulting in negative abnormal returns. The rationale behind the hypothesis is that short sellers are informed. The research encompasses multiple event windows, pre-event and post-event, in order to accept or reject the first hypothesis. Moreover, a multi-factor analysis is provided in order to find robust results. Based on these performed analyses, we provide evidence that short sellers seem to be informed and can reap abnormal returns on their investments. Following an investment strategy in which an investor follows the disclosed net short positions seems to provide the short seller with abnormal returns in a short-term holding period. These findings are in line with other studies, such as Engelberg *et al.* (2012), Diether *et al.* (2009) and Jank and Smajlbegovic (2017), among others.

Prominent papers have provided analyses on short selling bans in both the United States and different European countries. For example, Boehmer *et al.* (2013) have examined short selling bans in the financial crisis and found that stocks subject to the ban suffered a severe degradation in market quality. This was evidence that supported earlier research provided by Diamond and Verrecchia (1987). Many other prominent papers are mostly in line with the idea that short selling bans are detrimental to financial markets, since short sellers can be seen as market stabilizers.

The second hypothesis states that European short selling bans in 2020 had a negative effect on liquidity, whilst the third hypothesis states that European short selling bans in 2020 had a negative effect on volatility. These hypotheses are examined by following methods that are used in previous studies and providing a Difference-in-Difference analysis (AFM, 2022; Beber & Pagano, 2013; Siciliano and Ventoruzzo 2020).

Regarding liquidity, we find that the Amihud liquidity measure shows that banned stocks during the ban period in France, Italy and Belgium have a greater negative impact on liquidity compared to the reference period (pre-ban). We find the same results when we use the quoted bid-ask spread as second liquidity measure. In other words, the implemented ban in these three countries seem to have a negative effect on the liquidity of stocks within the sample.

Regarding volatility, we constructed a Difference-in-Difference model in which the volatility during the ban period and after the ban was lifted is examined. The pre-ban period is used as reference period in the study, and this has given some interesting results.

First, we find that our first volatility measure (Vol5) shows that volatility for the full sample is negative during the banned period. Moreover, we find that for banned stocks the effect of the short selling ban had a larger negative effect. The results that volatility is lower for the banned stocks during the ban period seems logical, since short sellers were prohibited from short selling these stocks in the countries France, Italy, and Belgium. The rationale behind this is that short sellers trade in the opposite direction, hence, when this type of investor disappears from the market there is less downward pressure on stock prices. Moreover, the Garman and Klass measures appear to support these results. These findings are in line with several academic papers (AFM, 2022; Siciliano and Ventoruzzo 2020), and in contrast with the findings of Beber & Pagana (2013), who investigated the effect on volatility during the financial crisis. These results should be interpreted with a large amount of consideration, since we find contradicting evidence with regards to papers that have investigated short selling bans during other crises. On the other hand, the results look as if they are in line with other findings on the effects of short selling bans on volatility during Covid-19.

All in all, this paper especially finds economic and significant results when examining the performance on disclosed net short positions in European countries, as well as the effects of the short selling ban on liquidity in 2020 in France, Italy and Belgium. Nonetheless, this paper is unable to accept the third hypothesis, stating that short selling bans have a negative impact on volatility. Reaching conclusions by thoroughly constructing and examining a dataset. we reason that short sellers are able to derive abnormal returns, as well as the significant negative effects of short selling bans on liquidity

Regarding the data of this paper a few limitations can be pointed out. This study was only able to use unique entry dates and did not account for subsequent net short positions by a certain short seller, nor did we account for exits. This results in a large loss of original data; hence, this could be recommended to provide in further research. The implications a dataset that accounts for all holdings would have far greater implications for the performance of disclosed net shorted positions. Such a study could build upon this study and on the research from Jank and Smajlbegovic (2017) by providing lucrative investing strategies and assess the behavior that short sellers show in Europe.

This paper also does not discuss the determinants of the reaped benefits by short sellers that are known as informed traders. In other words, one could provide an analysis that is more in line with Engelberg *et al.* (2012) and examine how short sellers are informed in European markets. For instance, this would suggest an analysis in which on would try to find the relation between certain public announcements and the Cumulative Abnormal Returns.

For future research it would be curious to extend the analysis by giving a deeper understanding on the effects that occur during short selling bans. For instance, Tilfani *et al.* (2021) study the relationship between variables, which could be applied in the study on the effects on market quality. Moreover, future research can expand the research by providing a sectorial analysis which gives academics and regulators a better understanding of the effects across different sectors, since the ban that leaded from Covid-19 was not a ban that was imposed on a certain industry. In addition, one could also examine the effects that disclosed net short positions have on the long term.

7. Appendix

Table 2: SIC codes

Range of SIC Codes		Division
0100-0999	1	Agriculture, Forestry and Fishing
1000-1499	2	Mining
1500-1799	3	Construction
1800-1999	4	not used
2000-3999	5	Manufacturing
4000-4999	6	Transportation, Communications, Electric, Gas and Sanitary service
5000-5199	7	Wholesale Trade
5200-5999	8	Retail Trade
6000-6799	9	Finance, Insurance and Real Estate
7000-8999	10	Services
9100-9729	11	Public Administration
9900-9999	12	Non-classifiable
	13	Unknown

Notes. List extracted from Wikipedia showing the SIC codes.

Table 3: Distribution of disclosed net short positions per industry sorted on countries (in percentages)

	0100 - 0999	1000 - 1499	1500 - 1799	2000 - 3999	4000 - 4999	5000 - 5199	5200 - 5999	6000 - 6799	7000 - 8999	N/A
AT	0,00	0,00	4,76	55,78	0,00	10,20	6,80	22,45	0,00	0,00
BE	0,00	10,26	0,00	47,25	16,48	0,00	5,49	7,69	12,82	0,00
DE	0,02	2,36	2,46	42,67	10,07	3,18	9,54	15,71	13,98	0,00
DK	0,00	0,00	0,89	55,08	11,25	0,13	1,79	12,78	18,08	0,00
ES	0,00	0,00	29,26	19,43	20,09	0,00	0,22	11,35	19,65	0,00
FI	0,00	0,00	33,33	54,89	1,81	0,00	2,72	1,99	5,25	0,00
FR	0,00	5,38	0,82	35,95	11,43	2,02	7,85	8,00	28,55	0,00
IE	8,47	0,00	0,00	49,15	5,08	0,00	0,00	16,95	20,34	0,00
ITA	0,00	0,25	8,04	36,81	9,30	1,76	6,66	32,16	4,40	0,63
NL	0,00	15,45	6,32	25,28	8,29	0,70	1,97	23,17	16,29	2,53
PL	0,00	7,63	0,76	14,50	7,63	10,69	14,50	19,08	24,43	0,76
POR	0,00	0,00	11,59	2,90	68,12	0,00	8,70	8,70	0,00	0,00
SE	0,26	0,19	8,21	45,05	4,72	0,58	10,86	6,21	23,79	0,13
UK	0,25	6,20	5,77	21,42	9,58	1,46	17,24	15,05	22,88	0,15

Notes. This table shows the distribution of disclosed net short positions by industries. We find the SIC-codes in the SIC codes table 2.

Table 5: leading indexes from European countries

Index	Country	Datastream code
CAC 40 Index	France	FRCAC40
FTSE 100	United Kingdom	FTSE100
ISEQ Overall Index	Ireland	ISEQUIT
Warsaw Stock Exchange WIG Index	Poland	POLWIGI
OMX Copenhagen 25	Denmark	COSEASH
OMX Stockholm PI	Sweden	SWSEALI
MSCI Italy Index	Italy	MSITALL
AEX	Netherlands	AMSTEOE
BEL 20	Belgium	BGBEL20
MSCI Finland Index	Finland	MSFINDL
DAX Performance	Germany	DAXINDX
IBEX 35 Index	Spain	IBEX35I

Notes. Country indexes used for the market model

Table 6: Two-sample t-test (un-)matched sample

	Obs. 1	Obs. 2	Mean 1	Mean 2	Difference	SE	t-value	p-value
ln avg mv	878	666	21.303	19.986	1.316	.097	13.65	0
ln avg mv	465	465	20.847	20.826	.021	.116	.2	.858

Notes: This table provides a two-sample t-test which is used to compare the means of two groups (matched sample vs unmatched sample). In this table the two-sample t-test compares Mean 1 and Mean 2 for the natural logarithmic of average market value (ln avf mv)

Table 8: Descriptive statistics of stock-level Fixed Effects for Coarsened Exact Matching sample

Variable	Unbanned Sample (ban = 0)				Banned Sample (ban = 1)			
	N	**Mean**	**Median**	**SD**	**N**	**Mean**	**Median**	**SD**
Analyst coverage	465	0.77	1.00	0.41	465	0.88	1.00	0.34
D/E ratio	461	1.11	0.61	1.57	457	1.24	0.82	1.63
ROA	459	2.89	3.37	11.07	452	0.70	2.14	12.03
Firm size	461	21.19	20.96	2.22	457	21.48	21.29	2.18

Notes. This table provides the descriptive statistics for stock-level fixed effect variables for the CEM sample consisting of 930 firms. N is the number of firms in the sample. Analyst coverage equals one when a stock is covered in the sample period and zero otherwise. D/E is the debt-to-equity ratio, ROA is return on assets and Firm size is the natural logarithmic value of reported total assets.

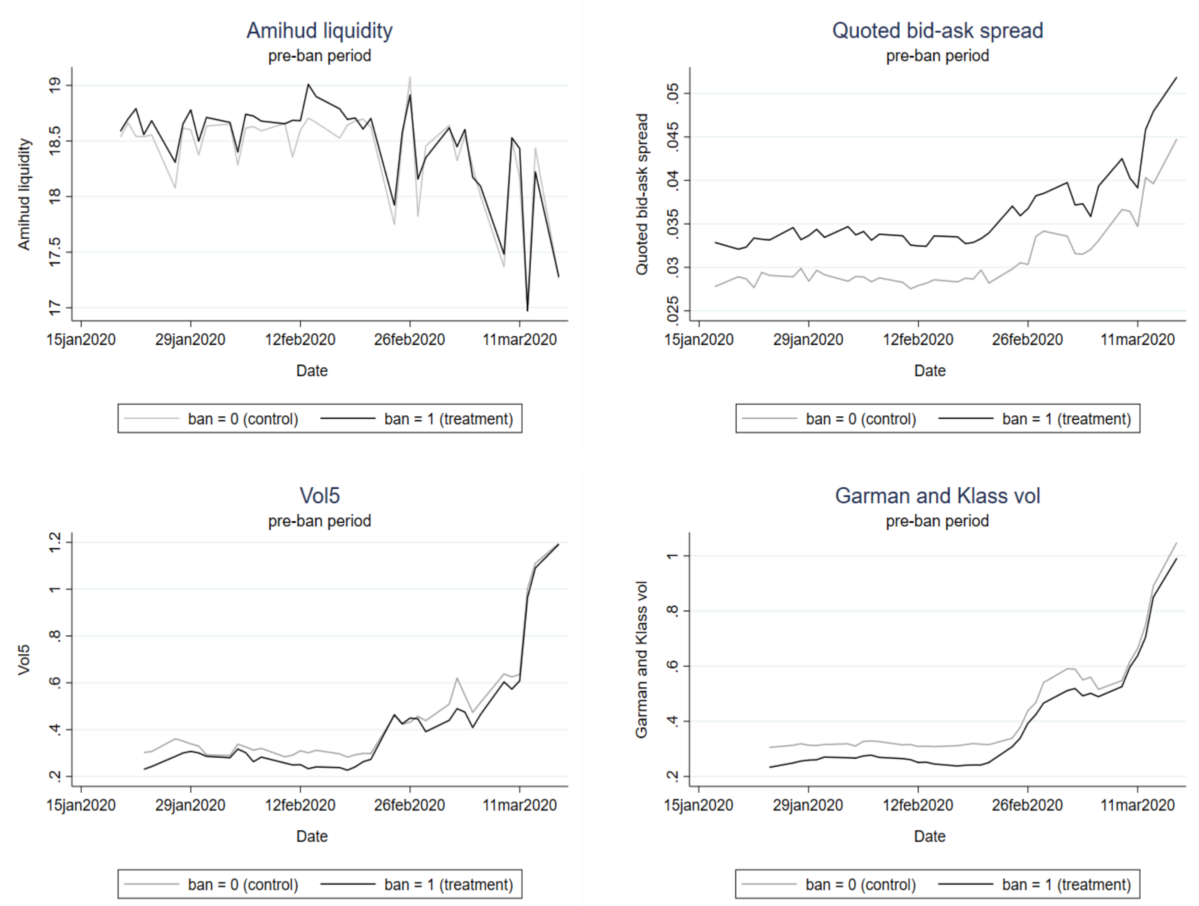

Figure 4: graphs on mean values for all dependent variables in the pre-ban period. These graphs are used to support the parallel trend assumption for the Difference-in-Difference analysis for hypothesis two and three. The unbanned sample is when ban=0, also known as the control group, whereas, the banned sample is when ban=1, also known as the treatment group.

Table 9: Two-sample t-test parallel trend assumption

	Obs.	Mean 1	Mean 2	Difference	SE	t-value	p-value
Amihud Liquidity	41	18.395	18.48	-.085	.093	-.9	.364
Quoted bid-ask spread	42	.031	.036	-.005	.001	-5.6	0
Vol5	38	.445	.404	.041	.052	.8	.435
Garman & Klass Vol	37	.436	.382	.054	.043	1.25	.213

Notes: This table provides a two-sample t-test which is used to compare the means of two groups (matched sample vs unmatched sample). In this table the two-sample t-test compares Mean 1 and Mean 2 for the natural logarithmic of average market value (ln avf mv)

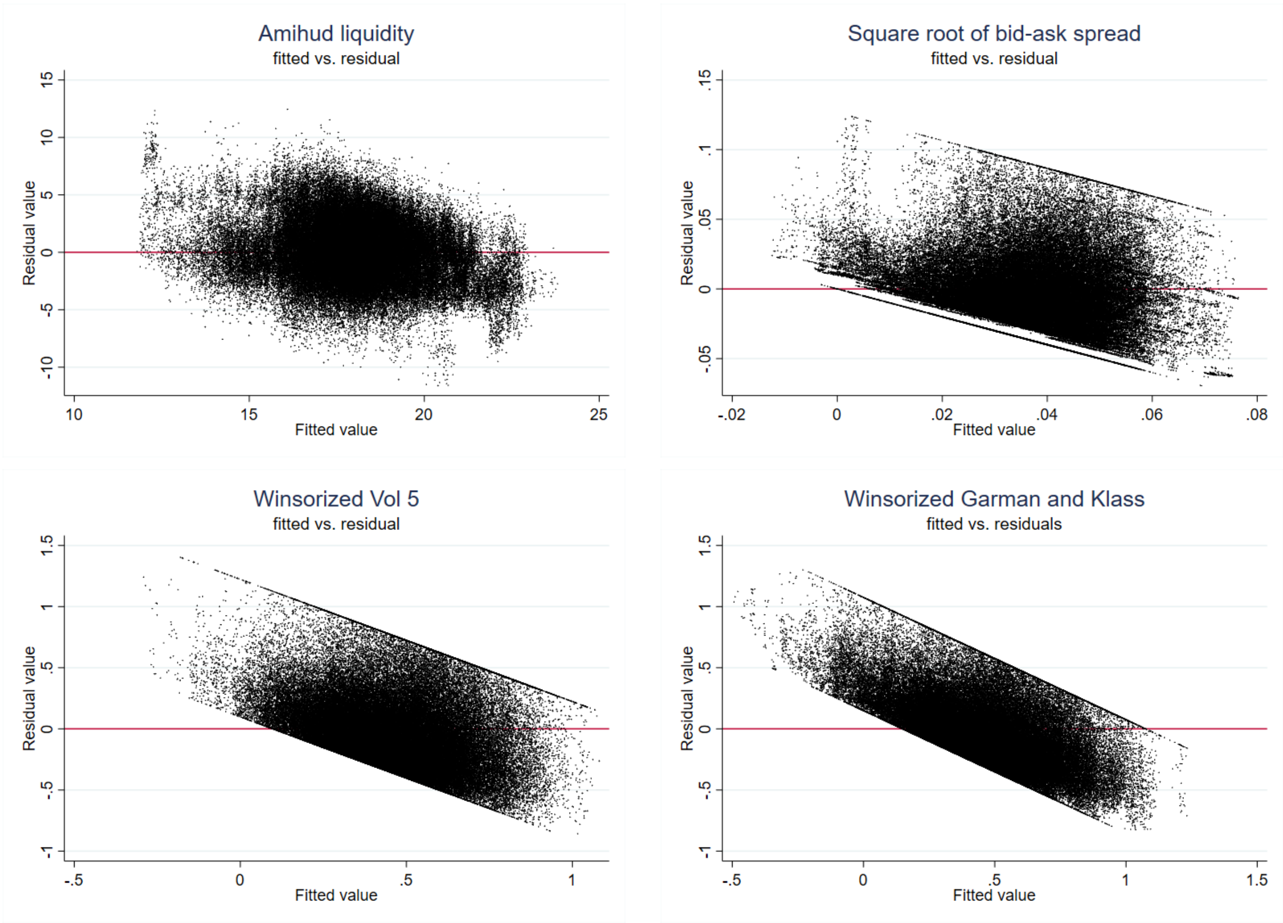

Figure 5: residual vs. fitted graphs testing heteroskedasticity for all dependent variables.

Table 17: pairwise correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Amihud liquidity	1.000											
(2) Bid-ask spread	-0.672***	1.000										
(3) Vol5	-0.116***	0.096***	1.000									
(4) Garman Klass Vol	-0.086***	0.126***	0.699***	1.000								
(5) Ban	0.003	0.125***	-0.086***	-0.102***	1.000							
(6) Pre	0.071***	-0.085***	-0.096***	-0.154***	-0.004	1.000						
(7) During	-0.085***	0.109***	0.265***	0.336***	-0.003	-0.484***	1.000					
(8) Post	0.014***	-0.023***	-0.168***	-0.183***	0.007**	-0.513***	-0.504***	1.000				
(9) B/M ratio	-0.095***	0.071***	0.015***	0.005	0.152***	-0.086***	0.086***	0.001	1.000			
(10) Stringency	-0.078***	0.124***	0.191***	0.256***	0.134***	-0.866***	0.600***	0.267***	0.119***	1.000		
(11) $R_{i, t-1}$	0.008**	-0.012***	-0.032***	-0.049***	-0.004	-0.131***	0.050***	0.079***	-0.035***	0.088***	1.000	
(12) $VSTOXX_{i, t-1}$	0.028***	-0.009***	0.024***	-0.003	-0.005	0.247***	-0.132***	-0.111***	-0.013***	-0.208***	-0.406***	1.000

Notes. This table represents a pairwise correlation matrix between dependent and independent variables used in the Difference-in-Difference analysis

8. References

AFM, A. (2022). French and dutch market authorities publish analysis of impact temporary french short sell ban in 2020. Retrieved from https://www.afm.nl/en/sector/actueel/2022/februari/onderzoek-verbod-short-sell

Aitken, M. J., Frino, A., McCorry, M. S., & Swan, P. L. (1998). Short sales are almost instantaneously bad news: Evidence from the australian stock exchange. *The Journal of Finance, 53*(6), 2205-2223.

Aktas, N., de Bodt, E., & Cousin, J. (2007). Event studies with a contaminated estimation period. *Journal of Corporate Finance, 13*(1), 129-145.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, 1, 1053-1128.

Battalio, R. H., Mehran, H., & Schultz, P. H. (2012). Market declines: What is accomplished by banning short-selling?. *Current Issues in Economics and Finance*, 18(5).

Beber, A., & Pagano, M. (2013). Short-selling bans around the world: Evidence from the 2007–09 crisis. *The Journal of Finance, 68*(1), 343-381.

Benhami, K., van Veldhuijzen, L., & Schoolderman, T. (2022). Short selling ban impact – a comparison of the french and the dutch markets. *Afm,* Retrieved from https://www.afm.nl/nl-nl/nieuws/2022/februari/onderzoek-verbod-short-sell

Bessler, W., & Vendrasco, M. (2021). The 2020 european short-selling ban and the effects on market quality. *Finance Research Letters, 42*, 101886.

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). Cem: Coarsened exact matching in stata. *The Stata Journal, 9*(4), 524-546.

Boehmer, E., Jones, C. M., & Zhang, X. (2008). Which shorts are informed? *The Journal of Finance, 63*(2), 491-527.

Boehmer, E., Jones, C. M., & Zhang, X. (2013). Shackling short sellers: The 2008 shorting ban. *The Review of Financial Studies, 26*(6), 1363-1400.

Boehmer, E., & Song, W. (2020). Smart retail traders, short sellers, and stock returns. *Short Sellers, and Stock Returns (October 23, 2020),*

Bris, A. (2008). Short selling activity in financial stocks and the SEC july 15th emergency order. *Retrieved August, 1*, 2010.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*(1), 57-82.

Chen, H., Zhu, Y., & Chang, L. (2019). Short-selling constraints and corporate payout policy. Accounting & Finance, 59(4), 2273-2305.

Chang, E. C., Cheng, J. W., & Yu, Y. (2007). Short-sales constraints and price discovery: Evidence from the hong kong market. *The Journal of Finance, 62*(5), 2097-2121. doi:10.1111/j.1540-6261.2007.01270.x

Coutts, J. A., Mills, T. C., & Roberts, J. (1994). The market model and the event study method: A synthesis of the econometric criticisms. *International Review of Financial Analysis, 3*(2), 149-171.

Daouk, H., & Charoenrook, A. A. (2005). A study of market-wide short-selling restrictions. *Available at SSRN 687562,*

Dechow, P. M., Hutton, A. P., Meulbroek, L., & Sloan, R. G. (2001). Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics, 61*(1), 77-106.

DeMarzo, P. M., Fishman, M. J., & Hagerty, K. M. (1998). The optimal enforcement of insider trading regulations. *Journal of Political Economy, 106*(3), 602-632.

Desai, H., Ramesh, K., Thiagarajan, S. R., & Balachandran, B. V. (2002). An investigation of the informational role of short interest in the nasdaq market. *The Journal of Finance, 57*(5), 2263-2287.

Diamond, D. W., & Verrecchia, R. E. (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics, 18*(2), 277-311.

Diether, K. B., Lee, K., & Werner, I. M. (2009). Short-sale strategies and return predictability. *The Review of Financial Studies, 22*(2), 575-607.

Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics, 105*(2), 260-278.

European Securities and Markets Authority. (2022). *The 2020 short selling bans – market impact*. Retrieved from https://www.esma.europa.eu/sites/default/files/library/esma50-165-2033_-_the_2020_short_selling_bans.pdf

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2), 383-417.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2), 427-465.

Figlewski, S. (1981). The informational effects of restrictions on short sales: Some empirical evidence. *Journal of Financial and Quantitative Analysis*, *16*(4), 463-476.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics, 111*(1), 1-25.

Galema, R., & Gerritsen, D. (2019). The effect of the accidental disclosure of confidential short sales positions. *Finance Research Letters, 28,* 87-94.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of Business,* , 67-78.

Hausman, J. A., & Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica: Journal of the Econometric Society,* , 1377-1398.

Ho, G. K. F., Treepongkaruna, S., Wee, M., & Padungsaksawasdi, C. (2022). The effect of short selling on volatility and jumps. *Australian Journal of Management*, *47*(1), 34-52.

Jank, S., Roling, C., & Smajlbegovic, E. (2021). Flying under the radar: The effects of short-sale disclosure rules on investor behavior and stock prices. *Journal of Financial Economics, 139*(1), 209-233.

Jank, S., & Smajlbegovic, E. (2017). Dissecting short-sale performance: Evidence from large position disclosures. *Available at SSRN 2631266,*

Jones, C. M., Reed, A. V., & Waller, W. (2016). Revealing shorts an examination of large short position disclosures. *The Review of Financial Studies, 29*(12), 3278-3320.

Karpoff, J. M., & Lou, X. (2010). Short sellers and financial misconduct. *The Journal of Finance, 65*(5), 1879-1913.

Lamont, O. A. (2004). Short sale constraints and overpricing. *NBER Reporter Online,* (Winter 2004/05), 16-18.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13-39.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance, 32*(4), 1151-1168.

Mitchell, M., Pulvino, T., & Stafford, E. (2004). Price pressure around mergers. *The Journal of Finance, 59*(1), 31-63. doi:10.1111/j.1540-6261.2004.00626.x

Ofek, E., & Richardson, M. (2003). Dotcom mania: The rise and fall of internet stock prices. *The Journal of Finance, 58*(3), 1113-1137.

O'Sullivan, K., & Kinsella, S. (2012). Short selling restrictions in the EU. *Financial Regulation International, July,*

Pan, J.*Classes 4 and 5: Equity in the cross section.* (). Retrieved from https://en.saif.sjtu.edu.cn/junpan/slide_EAP/slide_EAP_Cross2.pdf

Qin, S. (2011). Comparing the matching properties of Coarsened Exact Matching, Propensity Score Matching, and Genetic Matching in a nationwide data and a simulation experiment. *University of Georgia. ATHENS, GEORGIA.*

Saffi, P. A., & Sigurdsson, K. (2011). Price efficiency and short selling. *The Review of Financial Studies, 24*(3), 821-852.

Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*. Oup Oxford.

Securities, U. S., & Exchange Commission. (2008). SEC halts short selling of financial stocks to protect investors and markets. *SEC.Gov.Retrieved August, 11*(2012), 2008-2211.

Senchack, A. J., & Starks, L. T. (1993). Short-sale restrictions and market reaction to short-interest announcements. *Journal of Financial and Quantitative Analysis, 28*(2), 177-194.

Siciliano, G., & Ventoruzzo, M. (2020). Banning cassandra from the market? an empirical analysis of short-selling bans during the covid-19 crisis. *European Company and Financial Law Review, 17*(3-4), 386-418.

Staley, K. F. (1996). *The art of short selling* John Wiley & Sons.

The Netherlands Authority for the Financial Markets. (2015). Three years short sell regulation. Retrieved from www.AFM.nl

Tilfani, O., Ferreira, P., & El Boukfaoui, M. Y. (2021). Dynamic cross-correlation and dynamic contagion of stock markets: A sliding windows approach with the DCCA correlation coefficient. *Empirical Economics,* 60(3), 1127-1156.

U.S. Securities and Exchange Commission. (2010). Regulation SHO, release no. 34-63247. Retrieved from https://www.sec.gov/rules/final/2010/34-63247.pdf

Wilcoxon, F. (1992). *Individual comparisons by ranking methods* Springer.

Zuckerman, G. (2008). Are Hedge Funds Root of All Evil or Convenient Scapegoats?: Wall Streeters Urge Regulators to Apply Heat to Managers. *Wall Street Journal (1923)*