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The Effects of a Short Selling Ban on the Stock Market

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Preface and acknowledgements
In this research I had the challenge to apply everything i have learned over the past years during my study. I would like to thank Dr. Lemmen for his supervision along the way and very useful comments.

Abstract

This paper investigates the effect of a short selling ban on stock prices, returns and liquidity. This is done by applying a difference-in-differences methodology on a sample of Dutch and Belgian stocks. The research question is: What are the effects of a short selling ban on the stock market. It was found that the enactment of a short selling ban supports stock prices, but it was also found that it is related with an underperformance of banned stocks in terms of abnormal returns. There was no significant relationship found between the enactment of a short selling ban and liquidty, except for large-cap stocks for which a negative relationship was found.

Keywords: Short selling, short selling ban, liquidity, returns, difference-in-differences

Table of contents

1. Introduction

In March 2020, the Novel Coronavirus spread to a global pandemic. As a result, equity prices plummeted around the world (Baker et al., 2020). Regulators of several countries responded to this market crash by imposing temporary short selling bans (Matthews et al., 2021). Regulators from other countries, for example the UK and Germany, did not impose a short selling ban. In their opinion there is no evidence that short selling exacerbates the market crash, and they emphasize the importance of short sellers in providing liquidity and market efficiency. So, there is a dichotomy between countries that are for imposing a short selling ban and countries that are against it.

In the literature there is also no consensus on the effectiveness of short selling bans. In several crises over the years short sellers have been blamed for stock market declines. Short selling restrictions have been used to regulate short selling during uncertain times for a very long time, but the empirical evidence that proves the effectiveness of short selling bans is minimal. There are even various papers that disprove the effectiveness of short selling bans (Bris et al., 2007). I want to contribute to the literature by investigating the effect of a short selling ban on the stock market during the lockdown period, which was caused by the COVID-19 crisis. Therefore, the research question is:

Research question: What are the effects of a short selling ban on the stock market?

Most of the existing literature that investigates the effect of a short-selling ban on the stock market, examines short selling bans during earlier crises like the financial crisis of 2008. This makes it academically relevant to investigate the effect of a short selling ban during the market crash caused by the COVID-19 crisis, because the data is more recent. I also add to the literature by investigating the effect of a short selling ban with a difference-in-differences technique in conjunction with the setting of a natural experiment where Belgium decides to impose a short selling ban and the Netherlands decides not to. Also, I examine the effect of a short selling ban on both stock prices and abnormal returns in order to be able to compare the results. And lastly, I compare the effectiveness of short selling bans between subsamples based on market capitalization as used by Euronext, in order to assess the difference in effects of a short selling ban on the liquidity and performance of stocks with different market capitalization.

The fact that during the market crash in March 2020 there were both countries that did impose a short selling ban and countries that did not, makes this topic also societal relevant. There is no consensus between regulators from different countries whether a short selling ban is a good thing or not. By investigating the effect of a short selling ban during the COVID-19 market crash, regulators can get useful insights on the effects of a short selling ban and use these results to make a well-considered decision in the future when a similar crisis occurs.

The findings of this paper can be split into two parts. Firstly, it was found that the enactment of a short selling ban supports stock prices. However, it was also found that the enactment of a short selling ban is related with an underperformance of banned stocks in terms of abnormal returns. Secondly, I found no significant relationship between the enactment of a short selling ban and liquidity, when using a variety of stocks in terms of size. For large-cap stocks, it was found that the enactment of a short selling ban is associated with a decrease in liquidity.

The remainder of this paper is built up as follows: Chapter 2 describes the existing literature on short selling and short selling bans. Chapter 3 describes the data and methodology. Chapter 4 presents the results and discusses its robustness and limitations. Finally, chapter 5 provides a conclusion and summary of the paper.

2. Literature review and hypothesis development

2.1. Short selling

Short selling is a type of trading where an investor sells a stock that one does not own. The investor borrows it from a broker-dealer, an institutional investor or a brokerage house (Dechow et al., 2001). To close the position, the investor buys the stock back at a later time and gives the shares back to the lender. This particular type of short selling is called conventional or covered short selling. There is also naked short selling where an investor does not even borrow the share (Gruenewald, Wagner and Weber, 2009). So, in this case the short seller does not deliver the share back at the settlement date. In a naked short sale, the share sold short does not even exist sometimes.

The profit made by a short seller is the price of the share at the time the share was sold minus the price at the time the share was bought back, so a short seller profits from a decrease in the stock price. Obviously, the investor can also make a loss if the share has to be bought back at a higher price than it was sold for. This means that the loss for a short seller is potentially unlimited, because there is no limit in the increase in the price of a stock. This also makes a short sale riskier than a regular long position (Dechow et al., 2001). Despite the higher risk involved in short selling, on average short selling accounts for about more than 20% of trading volume in most markets (Boehmer, Jones and Zhang, 2008).

Because short sellers profit from decreases in stock prices, they try to identify stocks that will underperform the market in the future (Dechow et al., 2001). They identify overpriced stocks by looking at the ratios of fundamentals to market prices, such as the book-to-market and earnings-to-price ratio. Ideally, short sellers establish the short positions when fundamental-to-price ratios are low and then unwind their positions when the ratios revert to normal levels. This way, short sellers should end up with a profit. Boehmer, Jones and Zhang (2008) show the positive side of this trading strategy. They conclude from their results that short sellers, in particular institutional short sellers, trade on value-relevant information that has not been incorporated into stock prices yet. The effects on stock prices have shown to be permanent, which shows that short sellers are not manipulating stock prices. In fact, this shows that short sellers' trades contribute to more efficient stock prices. This is why short sellers are generally characterized as sophisticated and informed investors who play an important role in keeping the price of stocks in line with their fundamentals (Dechow et al., 2001)

Although most financial economists consider short sellers to be the 'good guys', short selling also has proven to have some negative sides (Dechow et al. (2001). Bliss, Molk, and Partnoy (2020) explain the strategy of operational negative activists. This kind of activists establish a short position on a stock and then try to damage the underlying company through spreading negative and inaccurate information about the company. This way they try to harm the profitability of a company and drive down the stock price. The only goal of this strategy is to increase the activists' profits, and this has nothing to do with driving the stock price to its fundamentals. This strategy has become a lot easier and more accessible with the rise of the internet and social media (Siciliano and Ventoruzzo, 2020). Anyone can establish a short position and then spread false information and rumours about a company on social media channels. These rumours can create a panic and a run from the stock if they get picked up by a large audience. This results in a falling stock price and profits for short sellers.

Another term that is often used when short selling is used to harm companies is predatory short selling. Especially financial institutions are vulnerable to predatory short selling. If the stock of financial institution is heavily shorted, the institution might have to be forced to liquidate long-term investments at very low prices, because of leverage constraints (Brunnermeier and Oehmke, 2014). Short sellers can try to bring down financial institutions by shorting the stocks to create a downward spiral in stock prices and make a profit themselves. Large banks such as Lehman Brothers and Morgan Stanley blamed short sellers during the financial crisis of 2008 for their distress.

2.2. Short selling regulation

As described before, short selling is associated with high risk, and it has the potential to be used to manipulate stock prices. That is why short selling is regulated in most countries. Short selling is regulated by the European Securities and Markets Authority (ESMA) on a European level (Regulation (EU), 2012). In 2012 the ESMA introduced a short selling register, which aims to enhance the transparency of short positions held by short sellers. For investors this means that their net short positions in shares have to be reported to the relevant competent authority of a country if they reach 0.2% of the issued share capital and their net short positions will get disclosed to the public if they reach 0.5% of the issued share capital. Also, since 2012 all short sales of shares must be covered, which means that naked short selling is banned for all countries that are regulated by the ESMA.

On top of the short selling restrictions already in place, the ESMA grants the competent authorities of individual countries the power to temporarily restrict short selling of securities (Della Corte et al., 2021). National competent authorities can temporarily ban short selling when a company is under attack by predatory short sellers (Marsh and Payne, 2012). For example, the supervisory authority of Germany implemented a temporary ban on short selling the shares of Wirecard AG for two months in 2019, because the authority suspected manipulation in the stock price of Wirecard AG (Matthews et al., 2021).

National competent authorities can also implement short selling bans to prevent panic on the stock market during uncertain times such as during a crisis. As a reaction to market crashes caused by the financial crisis in 2008 and the COVID-19 crisis in 2020, many countries implemented temporary short selling bans. These bans can differ a lot in coverage of the financial markets and specifications.

The bans during the financial crisis in 2008 mostly targeted financial stocks, because financial institutions were vulnerable during that crisis (Marsh and Payne, 2012). The bans introduced in March 2020 were mostly exchange-wide bans (Matthews et al., 2021). Short-selling bans also differ in which type of short selling they prohibit. Some short selling bans only target naked short sales, while the more stringent short selling bans prohibit both covered and naked short sales. Market-making and hedging activities are most of the time exempted from the ban (Boehmer, Jones and Zhang, 2009). Market makers can still sell short to provide liquidity to the market. This means that even when a short selling ban is in place, short selling activity does not decline to zero.

For this paper, the market crash in the beginning of 2020 caused by the COVID-19 crisis is central. In the beginning of 2020, the coronavirus outbreak had become a global pandemic (Baker et al., 2020). As a reaction, governments around the world restricted commercial activity and introduced social distancing, which had a huge impact on the economy. This shock to the economy also had a big impact on the stock market. No other infectious disease outbreak has had a bigger impact on the stock market as the COVID-19 pandemic. In March 2020 stock prices had decreased 25% on average compared to January 2020, which makes it one of the biggest market crashes in a century (Siciliano and Ventoruzzo, 2020). Besides, volatility was also extreme, which made it very uncertain times on the stock market.

As a reaction to this market crash, the ESMA temporary lowered the reporting threshold for short positions from 0.2% to 0.1% of the issued share capital, which made monitoring easier for regulators (Matthews et al., 2021). The ESMA did not implement additional short selling restrictions and let national competent authorities decide for themselves whether or not to implement additional short selling restrictions. Various countries such as Austria, Belgium, France, Spain and Italy responded to the market crash by Imposing mostly exchange-wide short selling bans. Other countries such as the United Kingdom and the Netherlands decided not to impose a short selling ban. The FCA, the supervisory authority in the United Kingdom, supported their decision by stating that there was no evidence that the market crash was caused by short sellers and pointed out the detrimental effect of a short selling ban on market liquidity (Matthews et al., 2021).

Belgium and the Netherlands are the central countries in this paper. The FSMA, the supervisory authority in Belgium, initially responded to the market crash by imposing a one-day short selling ban on 17 stocks that trade on the Euronext Brussels on the 16th of March 2020 (Matthews et al., 2021). One day later they decided to ban any transaction related to a financial instrument that would profit from the event of a decrease in the price, so from this point it was an exchange-wide short selling ban. The ban was originally in place until the 17th of April 2020, but it was extended on the 15th of April to the 18th of May. Market-making activities and index-related instruments of which relevant shares represented less than 20% of the index were exempt from the ban. In contrast to Belgium, the Netherlands did not impose additional restrictions in response to the market crash.

2.3. The effect of a short selling ban on stock prices and returns

I want to answer the research question by investigating the effect of a short selling ban on two aspects of the stock market. First, I want to examine the effect of a short selling ban on stock prices and returns. To form a hypothesis on the effect of a short selling ban on stock prices, it is interesting to first look at the relationship between short selling and stock returns. Diether, Lee and Werner (2009) examine data on daily short selling activity and abnormal returns for stocks trading on the New York Stock Exchange and the Nasdaq stock market during 2005. They find that increased short selling activity predicts negative subsequent abnormal returns. Boehmer, Jones and Zhang (2008) investigate the returns of heavily shorted stocks and lightly shorted stocks on the New York Stock Exchange from 2000 to 2004. They find that, on average heavily shorted stocks underperform lightly shorted stocks. Aitken et al. (2002) investigate the market reaction to short sales by conducting an event study on the occurrence of a short trades and subsequent abnormal returns on the Australian Stock Exchange. They find significant negative abnormal returns almost immediately following the initiation of short sales. All of the above results indicate negative subsequent returns as a reaction to an increase in short positions.

The main reason why regulators impose short selling bans is that they expect these bans to prevent financial panics (Beber and Pagano, 2013). According to Miller (1977) the rationale behind this is the decline in the number of optimistic investors due to funding constraints because of a crisis and short sellers that take advantage of the decreasing stock prices. These two factors together cause unjustified under-pricing of stocks. Regulators want to prevent this under-pricing by imposing restrictions on short selling. But as mentioned before, it is not sure whether it is justified or not to blame short sellers for stock market declines (Bris et al., 2007). This makes it questionable if imposing a short selling ban is the right thing to do.

The existing literature is divided on the topic. Bris et al. (2007) try to find an explanation for the relationship between short selling restrictions and stock returns based on the skewness of market returns. They find that the lifting of a short selling ban is associated with increased negative skewness in market returns. Their results indicate that extreme returns are more negative without short selling restrictions in place. This would suggest that a short selling ban can mitigate a market crash. Saffi and Sigurdsson (2010) also find increased negative skewness in market returns when short selling restrictions are not in place. But in contrast to what Bris et al. suggest (2007), Saffi and Sigurdsson (2010) find that the increased negative skewness is linked with less-frequent extreme positive returns rather than with more extreme price decreases.

The results of recent studies on the effects of short selling bans during the financial crisis of 2008 are somewhat contradictory as well. Boehmer, Jones and Zhang (2009) investigate the effects of a short selling ban imposed in September 2008 in the United States. The ban targeted financial stocks and nearly 1000 financial stocks were subjected to the ban. They use a difference-in-differences methodology to isolate the effects of the short selling ban on financial stocks during the ban period. They find large increases in stock prices for stocks affected by short selling bans as a reaction to the announcement of the ban.

The study by Harris, Namvar, and Phillips (2009) builds on the study by Boehmer, Jones and Zhang (2009). Harris, Namvar, and Phillips (2009) point out that the positive abnormal returns found by Boehmer, Jones and Zhang (2009) persist after the short selling ban was lifted. This makes it questionable if the positive abnormal returns were caused by the short selling ban. Harris, Namvar, and Phillips (2009) want to find out how much of the positive abnormal returns are caused by the short selling ban. Using a factor-analytic model and almost the same sample as Boehmer, Jones and Zhang (2009) they examine how much of the abnormal returns are associated with the short selling ban. They estimate that the prices of the banned stocks were inflated by 10.5% relative to where they would have traded without the short selling ban, based on the counterfactual created with their factor-analytic model. So, they confirm the results obtained by Boehmer, Jones and Zhang (2009).

Beber and Pagano (2013) try to identify the effects of different types of short selling bans imposed in various countries around the world during the 2008 crisis. They find a positive and significant response to the short selling ban for stock returns in the United States, which confirms the results of Boehmer, Jones and Zhang (2009) and Harris, Namvar and Phillips (2009). But, for the other countries in the sample they do not find a significant relationship between the enactment of short selling bans and stock returns. As a result, they conclude that short selling bans appear to have failed to support stock market prices.

The most recent studies on the effect of short selling bans on stock returns are conducted on short selling bans during the very recent COVID-19 crisis. Siciliano and Ventoruzzo (2020) examine the effects of short selling bans on stock prices and returns with a sample of fifteen European countries. They investigate the effects of short selling bans imposed in March 2020, as a reaction to the market crash in the beginning of 2020 caused by the COVID-19 crisis. Using a difference-in-differences identification strategy they find that stocks affected by a short selling ban significantly underperform non-banned stocks by 0.1% in terms of abnormal returns. This result is the opposite of the findings of Boehmer, Jones and Zhang (2009) and also exactly the opposite of what regulators want to achieve with imposing a short selling ban.

Le Moign and Spolaore (2022) investigate the effect of short selling bans on stock returns by doing research on 2464 EEA31 stocks (both European union countries and the UK) during the market crash in March 2020. They do this by measuring the impact of the bans on abnormal returns using a difference-in-differences regression. They find that the bans are linked with a decrease in abnormal returns. However, in contrast to the findings of Siciliano and Ventoruzzo (2020), this result is insignificant, so they conclude that the bans neither harm nor sustain market prices.

Benhami, van Veldhuizen and Schoolderman (2022) conduct a study on the impact of a short selling ban during the Covid crisis on various measures of market quality. They do this by conducting a difference-in-differences regression on a sample which consists of French and Dutch stocks, as the French authorities did impose a short selling ban whereas the Dutch authorities chose not to. With respect to returns they find that returns recovered after the enactment of the short selling ban. However, they do not find a significant difference between the French and Dutch sample in all examined periods.

Della Corte et al. (2021) focus more on the effects of short selling bans on the distribution of stock returns using summary statistics of stock returns as the dependent variables in a difference-in-differences regression. They investigate the effects of short selling bans imposed in March 2020. They use a sample which comprises observations between the 16th of February 2020 and the 15th of April 2020 for 17 European countries. They find a significantly lower mean and median in stock returns for banned stocks compared to non-banned stocks. But, they find significantly higher 10th 5th and 1st percentile stock returns for banned stocks compared to non-banned stocks. These results suggest that a short selling ban fails to support the average level of stock returns, but it is effective in altering the skewness of the distribution of stock returns. They conclude that a short selling ban supports the left tail of the distribution of stock returns, avoiding extreme negative returns. But, according to Saffi and Sigurdsson (2010), decreased negative skewness is not necessarily linked with less sharp decreases in returns.

Despite the contrary results from the literature, regulators still impose short selling bans with the expectation of preventing the stock market from being further driven down by short selling (Saffi and Sigurdsson, 2010). To investigate if this expectation is justified the following hypothesis is tested:

Hypothesis 1: There is a positive relationship between the enactment of a short selling ban and subsequent stock market returns and stock prices.

2.4. The effect of a short selling ban on liquidity

Secondly, I want to answer the research question by examining the effect of a short selling ban on another important aspect of the stock market, namely liquidity. One of the advantages of short selling is that short sellers provide market liquidity (Woolridge and Dickinson, 1994). They do this by shorting into up markets and reducing short positions in down markets. With a short selling ban in place, informed investors are prevented to trade on bad news (Diamond and Verrecchia, 1987). As a result, it takes longer until negative information is reflected in the price of a stock. This leads to more uncertainty about the fundamentals of a stock, causing the bid-ask spread to increase and thus liquidity to decrease, given that the bid-ask spread is a good proxy for liquidity.

Beber and Pagano (2013) came up with a different explanation for the relationship between a short selling ban and market liquidity, based on inventory holding costs. The bid-ask spread is a compensation for dealers for their inventory holding costs. When a short selling ban is in place, market makers are unable to short stocks and this impairs their inventory management. This is problematic, especially when markets are volatile for example in a crisis. As a result, market makers widen their bid-ask spreads. Also, as mentioned before, short selling bans make stock prices less informative because informed investors are prevented to trade on bad news. This makes it riskier to trade as an uninformed market participant. So, uninformed market makers will widen their bid-ask spreads to cover for their increased inventory holding costs (Bai, Chang and Wang, 2006)

Most of the evidence from the literature confirms the aforementioned relationship between a short selling ban and liquidity in the stock market. Boehmer, Jones and Zhang (2009) analyse the effect of a short selling ban that targeted financial stocks in the United States during the financial crisis of 2008. They use a Difference-in-differences methodology as described in Table 1. They find a significant increase in bid-ask spreads of 0.35% for financial stocks compared to non-financial stocks during the ban period. This means a significant deterioration in liquidity.

Marsh and Payne (2012) conduct similar research for the United Kingdom where the short selling ban also targeted financial stocks. By analysing order and transaction data they estimate the effect of the short selling ban on the bid-ask spreads and measures related to the depth of the limit order book. They find an additional increase of 17bp in bid ask spreads for financial stocks during the ban period compared to the non-financial stocks. In addition, they also find a decline in market depth for stocks affected by the ban, compared to stocks that were exempt from the ban. They show that the effects on liquidity were stable and consistent throughout the ban-period, so they conclude that the short selling ban was responsible for the deterioration in liquidity.

Beber and Pagano (2013) also investigate the effects of short selling bans on liquidity in 30 countries during the 2008 crisis. They use the bid-ask spread as a proxy for liquidity and a difference-in-differences methodology as described in Table 1. Furthermore, they also control for different kinds of short selling bans. They find a significant increase of 1.28 percentage points in bid-ask spreads associated with bans on naked short selling and a significant increase of 1.98 percentage points in bid-ask spreads associated with the more stringent bans on covered short selling. So, just like the before mentioned authors, they conclude that the short selling bans imposed in 2008 were detrimental for market liquidity.

In a more recent study, Siciliano and Ventoruzzo (2020) investigate the effect of short selling bans on liquidity during the COVID-19 crisis using the same sample and identification strategy as described in the previous section. They use the bid-ask spreads and the Amihud illiquidity measure as proxies for liquidity. They find that the liquidity, based on the Amihud illiquidity measure, of banned stocks is 0.1% lower compared to the liquidity of the same banned stocks in the pre-ban period and to non-banned stocks. They also find a significant increase of 16% in bid-ask spreads relative to non-banned stocks, which also means a decrease in liquidity.

Le Moign and Spolaore (2022) also investigate the effect of short selling bans on liquidity during the COVID-19 crisis. They use the bid-ask spread and the Amihud illiquidity indicator as proxies for liquidity and they use the same identification strategy and sample as they used to measure the impact of short selling bans on abnormal returns as described in the previous section. They find a significant increase of 7.5% of the bid-ask spread for banned stocks during the ban-period compared to the control group. Similarly, they also find a significant increase of 2.2% and 4.8% in the Amihud illiquidity indicator for banned stocks compared to non-banned stocks. As a result, they conclude that the effects of short selling bans on market liquidity appear to be negative.

Della Corte et al. (2021) investigate the effects of short selling bans on market liquidity during the COVID-19 pandemic, by only using the bid-ask spread as a dependent variable in a difference-in-differences regression. They use the sample and identification strategy as described in Table 1. They find that the average bid-ask spreads in countries that chose to impose short selling bans increased significantly by an additional 0.12% compared to countries that did not impose a short selling ban.

Benhami, van Veldhuizen and Schoolderman (2022) examine the effect of a short selling ban on liquidity during different periods in the beginning of 2020. They use various proxies for liquidity, amongst others the quoted bid-ask spread measured in basis points. Using the identification strategy as described in Table 1, they find a significant difference of 7 basis points in quoted bid-ask spreads between the French sample and Dutch sample during the ban period. However, they also find a difference of 6 basis points during the pre-ban period compared to the benchmark period, so the difference did not significantly increase after the short selling ban was enacted.

Bessler and Vendrasco (2021) conduct a study on the effect of the 2020 short selling ban on liquidity, using a sample of 12 European countries. They use different measures for liquidity compared to the aforementioned authors. They use a measure based on the bid-ask spread and market turnover called *Spreads at €10K* and a volume-based measure called *Turnover.* Using a panel regression, they find a significant and positive coefficient for the ban dummy in the regression with *Spreads at €10K* as the dependent variable and a significant and negative coefficient for the ban dummy in the regression with Turnover as the dependent variable. Both results indicate that the short selling ban had a negative effect on market liquidity.

As with the relationship between short selling bans and stock returns, there are also studies that find a different relationship between de enactment of a short selling ban and market liquidity. for example, Charoenrook and Daouk (2005) examine the effect of short selling bans on total stock market trading volume. They find a positive correlation between the imposition of short selling bans and total stock market trading volume. But according to Beber and Pagano (2013) trading volume is not a good proxy for liquidity during a crisis period, because wider bid-ask spreads can be associated with higher trading volumes during periods of uncertainty in the stock market. As most papers use the bid-ask spread as a proxy for liquidity I will also use the bid-ask spread as proxy and will test the following hypothesis:

Hypothesis 2: There is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market.

Table 1: Meta table of relevant literature related to the effects of short selling bans on liquidity and returns.

Author(s) (Publication year)	Time period	Region	Method	Control variables	Results
Boehmer, Jones and Zhang (2009)	01-08-2008 – 31-10-2008	United States	Difference-in-differences	Market cap, trading volume, transaction prices and VWAP. Firm FE and day FE	BAN = 0.0035*** (bid-ask spread as dep. Variable)
Harris, Namvar and Philips (2009)	18-09-2007 – 31-12-2008	United states	Factor-analytic model	Inverse price, turnover and volatility	10.5% return difference
Marsh and Payne (2012)	01-06-2008 – 28-02-2009	United Kingdom	Difference-in-differences	Volatility	17bp difference in increase in bid-ask spreads
Beber and Pagano (2013)	01-01-2008 – 23-06-2009	30 different countries	Differences-in-differences and Event study	Volatility and Disclosure. Stock-level FE	Covered Ban = 0.0611*** Naked Ban = 1.28*** Covered Ban = 1.98***
Siciliano and Ventoruzzo (2020)	24-01-2020 – 18-05-2020	Europe	Difference-in-differences	Volatility, stringency and Stock-level FE	Ban = -0.001*** (returns) Ban = -0.001*** (liquidity) Ban = 0.151*** (Bid-ask)
Le Moign and Spolaore (2022)	13-01-2020 – 30-06-2020	EEA31 (Europe and the UK)	Difference-in-differences	Fragmentation, market cap, volume, VSTOXX, Stringency Index and volatility. Stock FE and day FE	Treatment*Event = -0.005 Treatment*Event = 0.072*** Treatment*Event =0.022***
Della Corte et al. (2021)	17-02-2020 – 15-04-2020	Europe	Difference-in-differences	Only stock-level FE and day FE	Ban = 0.1172*** Ban = -0.0007*
Benhami, van Veldhuizen and Schoolderman (2022)	02-01-2020 – 15-06-2020	France and The Netherlands	Difference-in-differences	Market cap, Volatility and ratio. Firm and day FE	SSB X Banned = 9.9252 (returns) SSB X Banned = 7.1226*** (bid-ask)

Bessler and Vendrasco (2021)	02-01-2020 – 30-06-2020	12 European countries	Fixed-effects panel regression	Market cap, trading volume, volatility and VWAP. Stock-level FE	Ban = 0.1981*** Ban = -0.2762***

3. Data and Methodology

3.1. Data

The effects of a short selling ban on the stock market are investigated by examining a sample of stocks from Belgium and the Netherlands. Belgium imposed a short selling ban on the 17th of March which was in place until the 18th of May (Matthews et al., 2021). I collected stock market data from the 17th of January till the 18th of May, in order to have a pre-ban period and ban period of equal size in terms of trading days. The pre-ban period starts the 17th of January and ends the 16th of March and consists of 42 trading days. The ban period starts on the 17th of March and ends the 18th of May and consists of 42 trading days as well. As Belgium imposed a short selling ban on all stocks admitted to trading on the Euronext Brussels stock exchange, stock market data of all stocks trading on the Euronext Brussels are collected. This is done by downloading stock market data for all items of the total market index of Euronext Brussels available on Datastream. For the Netherlands the same stock market data is collected for all the items of the total market index of Euronext Amsterdam.

Table 2 shows the sample of stocks for the Netherlands and Belgium and how to arrive at the sample. The goal is to end up with a sample of only common stocks that trade on the Euronext Brussels and Amsterdam. To arrive at the sample, I excluded closed-end funds, Exchange-traded funds (ETF) and Real estate investment trusts (REIT). I also excluded stocks for which there was missing price data, because without this data it is impossible to calculate the bid-ask spreads and returns. Additionally, I dropped individual observations for which the daily return was zero. These zero returns were present in the data, because of non-trading on public holidays. Leaving these zero returns in could cause a bias (Beber and Pagano, 2013). For the same reason, observations with negative bid-ask spreads are dropped as well. As can be seen in Table 2, I ended up with a sample of 81 common stocks from the Euronext Brussels and 86 common stocks from the Euronext Amsterdam.

Table 2: Sample development of the Belgian and Dutch samples of stocks.

Selection criteria	Euronext Brussels stocks	Euronext Amsterdam stocks
Original Euronext list	175	186
Items of total market index on Datastream	133	120
Exclude Closed-end funds, ETF’s, REIT’s and stocks with missing price information.	81	86

The collected stock market data from Datastream consists of the daily stock, bid and ask prices, shares outstanding and the SIC industry code. All of this data is measured at the market close. Besides this stock market data, price levels of the total market indices of Belgium and the Netherlands are also obtained from Datastream, in order to be able to calculate abnormal returns. I also collected trading volume data for each individual stock from Datastream, but there was a lot of missing data for this variable. So, instead of using this data, I collected trading volume data from Yahoo finance. For the Dutch stocks the trading volume of the AEX index is used and for the Belgian stocks the trading volume of the BEL20 index is used. Information about the short selling ban and its specifications, such as enactment and lifting dates are obtained from Matthews et al. (2021).

Following most of the literature, I use the quoted bid-ask spread as a proxy for liquidity. This is the bid-ask spread quoted at the mid-price, which is the average of the bid price and the ask price. So, the quoted bid-ask spread is calculated as follows:

Quoted bid-ask spread = (bid price – ask price) / mid-price

The other dependent variables are the stock price and the abnormal return. Following Beber and Pagano (2013) and Siciliano and Ventoruzzo (2020), the abnormal return is measured as the difference between the daily return of a stock and the return on the country market index on the same day. So, the abnormal return is calculated as follows:

Abnormal return = return of stock i on day t – return on the country market index on day t

Tables 3, 4, 5 and 6 show the descriptive statistics of the variables used in the analysis. I split the sample by country and period, so Table 3 shows the descriptive statistics for Belgian stocks in the non-ban period, Table 4 for Belgian stocks in the ban period, Table 5 for Dutch stocks in the non-ban period and Table 6 for Dutch stocks in the ban period (based on when Belgium imposed the ban). As can be seen from the tables, the sample contains 3374 observations for Belgian stocks in the non-ban period and 3362 observations in the ban period, which add up to 6736 observations for Belgian stocks. The sample contains 3609 observations for Dutch stocks in the non-ban period and 3606 observations in the ban period, which add up to 7215 observations for dutch stocks. In total, the sample consists of 6983 observations in the non-ban period, 6968 in the ban period and 13951 for the entire sample period. The difference in observations between the non-ban period and the ban period is due to the dropped observations as explained in Table 2.

If one compares the tables for Belgium and the Netherlands, something that stands out is the difference in average stock price. The average stock price in the Belgian sample of stocks is way higher than in the Dutch sample, namely 165.007 in the non-ban period and 145.260 in the ban period compared to 43.416 and 36.933 for the Dutch sample. Also notable is the difference in average abnormal return between the two samples. The abnormal return is positive on average for the Belgian sample before the ban was imposed, while it is negative on average for the Dutch sample in the non-ban period. Also noteworthy, is the difference in the variable *Marketcap*, which is the market capitalization measured in thousands of euros. The average market capitalization for the Dutch sample is more than two times higher than for the Belgian sample, namely 7825387 compared to 3802366 in the non-ban period and 6691108 compared to 2948163 in the ban period. There is no big difference between the two samples in the variable *Q_Bid_Ask,* which is the quoted bid-ask spread. The same applies to the variable *Volatility,* which is the standard deviation of previous returns. How these variables are exactly calculated will be explained in the methodology section.

If one compares the non-ban period table with the ban period table for both countries, the following observations can be made. For the Belgian sample the average stock price decreases with 11.97% between the non-ban period and the ban period, while for the Dutch sample the average stock price decreases 14.93%. If one looks at the abnormal return variable, there is a decrease of 106.66 percent for the Belgian sample between the non-ban period and the ban period, while for the Dutch sample there is a decrease of 100%. So, for stock prices there is a larger decrease in the Dutch sample, while for abnormal returns there is a larger decrease in the Belgian sample. For the other variable of interest, *Q_Bid_Ask,* there is an increase of 60% in the quoted bid-ask spread for the Belgian sample between the non-ban period and the ban period, while for the Dutch sample there is an increase of 54.55%. So, for both countries there is a large increase in bid-ask spreads between the non-ban period and the ban period. The aforementioned numbers are already preliminary results.

Tables 3 to 6 also show the descriptive statistics of the returns on the total market indices of Belgian and the Netherlands, which are named *TotMrktIndexBE* and *TotMrktIndexNL.* If one compares the Tables for the Dutch sample with the tables for the Belgian sample, it can be seen that the Belgian total market index performs worse than the Dutch total market index in both periods. The average daily return on the Belgian index in the pre-ban period and ban period are respectively -1.1% and 0.4%, compared to -0.8% and 0.5% for the Dutch index. The returns on the Belgian index are also more volatile in both periods compared to the Dutch index, namely 0.3 and 0.026 versus 0.023 and 0.022. Lastly, comparing the pre-ban period tables with the ban period tables, it can be seen that the average daily return on the index was negative in the pre-ban period and positive in the ban period for both countries.

Table 3: Descriptive statistics of the variables for the Belgian sample of stocks in the non-ban period.

Variable	Observations	Mean	Std. Dev.	Min	Max	Median	Skewness
Price	3374	165.007	557.298	0.625	3900	44.988	5.136
Abnormalreturn	3374	0.003	0.024	-0.199	0.172	0.001	0.423
Q_Bid_Ask	3374	0.010	0.017	0.0001	0.307	0.004	5.859
Volatility	3374	0.017	0.015	0.003	0.134	0.013	2.288
Marketcap	3374	3802366	1.22e+07	57024	1.22e+08	993783.9	7.707
Tradingvolume	3374	38.684	24.265	10.72	101.73	26.14	1.092
TotMrktIndexBE	42	-0.011	0.300	-0.134	0.022	-0.001	-2.363

Table 4: Descriptive statistics of the variables for the Belgian sample of stocks in the ban period.

Variable	Observations	Mean	Std. Dev.	Min	Max	Median	Skewness
Price	3362	145.260	497.558	0.645	3290	34.035	5.029
Abnormalreturn	3362	-0.0002	0.035	-0.219	0.332	-0.002	0.860
Q_Bid_Ask	3362	0.016	0.026	0.0001	0.312	0.008	5.036
Volatility	3362	0.030	0.021	0.001	0.142	0.023	1.495
Marketcap	3362	2948163	8003242	28430.91	7.62e+07	812056.4	6.790
Tradingvolume	3362	48.876	16.372	29.8	118.51	47.23	1.973
TotMrktIndexBE	42	0.004	0.026	-0.048	0.067	0.005	-0.035

Table 5: Descriptive statistics of the variables for the Dutch sample of stocks in the non-ban period.

Variable	Observations	Mean	Std. Dev	Min	Max	Median	Skewness
Price	3609	43.416	95.613	0.805	893.9	19.79	6.623
Abnormalreturn	3609	-0.001	0.035	-0.477	0.825	-0.001	6.038
Q_Bid_Ask	3609	0.011	0.057	0.0001	1.902	0.002	6.545
Volatility	3609	0.021	0.022	0.003	0.371	0.015	6.054
Marketcap	3609	7825387	1.86e+07	3298.89	1.25e+08	1101199	4.327
Tradingvolume	3609	126.605	75.331	38.12	322.54	94.26	1.267
TotMrktIndexNL	42	-0.008	0.023	-0.101	0.023	0.002	-1.984

Table 6: Descriptive statistics of the variables for the Dutch sample of stocks in the ban period.

Variable	Observations	Mean	Std. Dev	Min	Max	Median	Skewness
Price	3606	36.933	95.426	0.768	1035.5	13.785	7.207
Abnormalreturn	3606	-0.002	0.041	-0.491	0.479	-0.003	0.576
Q_Bid_Ask	3606	0.017	0.051	0.0001	1.718	0.004	4.445
Volatility	3606	0.038	0.028	0.002	0.501	0.033	5.482
Marketcap	3606	6691108	1.75e+07	3145.215	1.34e+08	818796.8	4.795
Tradingvolume	3606	161.559	57.191	85.73	419.26	148.26	2.221
TotMrktIndexNL	42	0.005	0.022	-0.042	0.066	0.011	0.003

3.2. Methodology

As mentioned before some countries, for example Belgium, imposed a short selling ban during the 2008 stock market crash. Other countries chose not to impose a short selling ban, for example the Netherlands. A situation in which one country implements a sharp change in government policy and another country, similar in economic environment, does not implement this change, creates the setting of a natural experiment (Angrist and Pischke, 2008). A setting can be seen as a natural experiment when the treatment is not assigned randomly to the different groups. This is true for the situation that will be investigated in this paper. The regulators in Belgium decided themselves to take the treatment, in this case a short selling ban and the regulators in the Netherlands themselves chose not to impose a short selling ban. As Belgium imposed a short selling ban on all stocks admitted to trading on the Euronext Brussels stock exchange, all stocks that trade on the exchange and that are selected for the sample, are assigned to the treatment group. The fact that Belgium imposed an exchange-wide ban is also the main reason why Belgium is picked as the treatment group. All stocks that trade on the Euronext Amsterdam and that are selected for the sample are assigned to the control group.

3.2.1. Difference-in-differences

To investigate the effect of a short selling ban I will use a difference-in-differences technique. difference-in-differences is a quasi-experimental technique used to understand the effect of a sharp change in the economic environment or government policy (Angrist and Pischke, 2008), in this case a short selling ban. With the difference-in-differences strategy one can compare the change in a variable of interest in the treatment group with the change in the variable of interest in the control group, as reaction to the treatment. An important and positive feature of the difference-in-differences technique is that the difference-in-differences estimator controls for omitted common trends and for omitted cross-sectional differences between the treatment and control group (Angrist and Pischke, 2008).

Angrist and Pischke (2008) point out the importance of the parallel trends assumption when working with a difference-in-differences identification strategy. So, before the regression analysis I want to test if this assumption is violated. This assumption assumes that the trend of the dependent variable should be comparable for the control group and the treatment group in the pre-treatment era. This assumption is tested by testing if there is a difference in the average growth of the dependent variable over the pre-treatment era between the treatment and the control group. To be able to test this, I calculated the average percentage growth in de dependent variable for each day of the pre-treatment period for both groups. Then I took the average of the daily growth percentages and ended up with the average daily growth during the pre-treatment period for both the treatment sample of stocks and the control sample of stocks. Then I tested if these two averages differ from each other with a two-sided t-test. The following hypothesis and alternative hypothesis were tested:

H_0: mean (control group) = mean (treatment group)
H_a: mean (control group) ≠ mean (treatment group)

If the p-value of the t-test is higher dan 0.05, then the null-hypothesis cannot be rejected and that means there is no evidence to assume that the average daily growth differs between the treatment and control group. If this is the case, the equal trends assumption cannot be rejected, which means that the data is suitable for a difference-in-differences identification strategy.

3.2.2. Regression analysis for stock prices and returns

In this section, I will describe the methodology to test the following hypothesis: *There is a positive relationship between the enactment of a short selling ban and subsequent stock market returns and stock prices.*

I want to examine the effect of a short selling ban on both stock prices and returns. Instead of the raw return, I use the abnormal return which is calculated as described in the data section. Looking at the abnormal return of a stock, it is possible to assess a stock's performance relative to the performance of the overall market (Siciliano and Ventoruzzo, 2020). This can give usefull insights with respect to the performance of stocks that are affected by the short selling ban. If a banned stock outperforms the market, this can give an indication of the influence of a short selling ban on the performance of a stock.

For both variables I use the difference-in-differences regression as proposed by Angrist and Pischke (2008). This means that the abnormal returns will be regressed on three estimators. First, the treatment dummy variable called *Ban*. This variable takes on the value one if an observation is in the treatment group (Belgium), and thus is affected by the short selling ban, and zero if it is in the control group (the Netherlands). Secondly, the time dummy variable called *Event*. This variable takes on the value one if an observation is observed between the 17th of March (start of the ban) and the 18th of May (end of the ban), and zero if it is observed between the 17th of January and the 16th of March, the period before the ban. And thirdly, the difference-in-differences estimator called *EventXBan*, which is the variable of interest. This variable is an interaction variable which isolates the effect of the short selling ban on the banned stocks. This variable is calculated by multiplying the variable *Ban* and the variable *Event*. This way, the variable takes on the value one if an observation is in the treatment group and is observed during the ban period and takes on the value zero otherwise.

Besides these variables, I also added control variables. Following Boehmer, Jones and Zhang (2009) and Le Moign and Spolaore (2022), I controlled for firm size by including the variable *Marketcap*, which is the market capitalization measured in thousands of euros. The market capitalization of a company is calculated by multiplying the stock price with its total number of shares outstanding. As can be seen in Table 1, a lot of studies control for volatility in returns. Following the literature, I also included a measure for volatility. For the calculation of the variable *Volatility*, I used the method used by Beber and Pagano (2013). The variable *Volatility is* measured as the rolling standard deviation of the returns of a stock based on the previous 5 trading days.

Lastly, I also added trading volume as control variable, because more than 20% of trading volume is related to short selling (Siciliano and Ventoruzzo, 2020). It is thus expected that a short selling ban affects trading volume. Furthermore, there is a positive relationship between trading volume and contemporary stock returns, which makes it an important control variable (Pathirawasam, 2011). For Dutch stocks I used the trading volume of the AEX index and for Belgian stocks I used the trading volume of the BEL20 index. Both are measured in thousands of Euros. In the difference-in-differences regressions, all possible combinations of control variables are tested.

It is common in the literature to take the natural logarithm of some variables. This log transformation deals with the skewness of the distribution of a variable by reeling the values more into the centre of the distribution (Siciliano and Ventoruzzo, 2020). This way the distribution is closer to a normal distribution, which makes it more suitable for a regression analysis. The log transformed data also deals better with potential outliers than the raw data. Skewness values between -1 and 1 indicate that a variable is normally distributed (Kim and White, 2004). As can be seen in Table 3 to 6, the skewness values for most of the variables used in the dataset are higher. The log transformation is applied to all variables used in the regressions, because after comparing the skewness values of the log transformed variables with the raw variables, it turned out that the skewness levels were closer to zero for the log transformed variables, for all variables used.

As I am dealing with panel data, the regression will also include firm-specific fixed effects to control for unobserved heterogeneity because of stock characteristics such as capitalization, risk, analyst coverage and number of market makers (Beber and Pagano, 2013). This way, cross-sectional variation is removed. When including both control variables and firm-specific fixed effects, the regression equation to test Hypothesis 1 looks like this:

$$Dependent\ variable_{it} = \beta_0 + \beta_1 Ban_{it} + \beta_2 Event_{it} + \beta_3 EventXBan_{it} + \beta_4 LnVolatility_{it} + \beta_5 LnMarketcap_{it} + \beta_6 LnTradingvolume_{it} + FE + \varepsilon_{it}$$

The regression equation with *LnPrice* as the dependent variable looks exactly the same as the regression equation with *LnAbnormal_return* as the dependent variable. Therefore, I only included one regression equation. Thus, *Dependent variable* stands for both the variables *LnPrice* and *LnAbnormal_returns.* On the right-hand side are the difference-in-differences variables *Ban, Event* and *EventXBan. EventXBan* is the difference-in-differences estimator and the variable of interest. The control variables are *LnMarketcap*, which is the natural logarithm of market capitalization, *LnVolatility*, which is the natural logarithm of the standard deviation of returns and *LnTradingvolume*, which is the natural logarithm of the trading volume of the respective index. Lastly, firm-specific fixed effects *FE* are added, which means the regression is estimated with robust standard errors clustered at the stock level.

3.2.3. Regression analysis for liquidity.

In this section, I will describe the methodology to test the second hypothesis: *Hypothesis 2: There is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market.*

Following most of the literature, I use the quoted bid-ask spread as a proxy for liquidity. The calculation of this variable can be found in the data section. This variable, just as *LnPrice* and *LnAbnormal_return*, is also regressed on the difference-in-differences estimators. The variable is also regressed on the same control variables as the before mentioned variables. Changing levels of stock price volatility affects the inventory risk of market makers (Siciliano and Ventoruzzo, 2020). This affects market liquidity, which makes it important to control for volatility. Following the literature, I also control for market capitalization, because it is found that the effect of a short selling ban on liquidity differs between stocks with different market capitalization. It is also of interest to control for trading volume, because as described before there is a positive correlation between the imposition of a short selling ban and total stock market trading volume (Charoenrook and Daouk, 2005). Furthermore, wider bid-ask spreads can be associated with higher trading volumes during periods of uncertainty in the stock market (Beber and Pagano, 2013).

As for *Abnormal_return*, I also use the natural logarithm of the quoted bid-ask spread, because of the before mentioned reasons. Again, the regression is executed with firm-specific fixed effects and the equation to test Hypothesis 2 looks as follows:

$$Ln\_Q\_Bid\_Ask_{it} = \beta_0 + \beta_1 Ban_{it} + \beta_2 Event_{it} + \beta_3 EventXBan_{it} + \beta_4 LnVolatility_{it} + \beta_5 LnMarketcap_{it} + \beta_6 LnTradingvolume_{it} + FE + \varepsilon_{it}$$

In this equation, *ln_Q_Bid_Ask* is the natural logarithm of the quoted bid-ask spread. *Ban, Event* and *EventXBan* are the difference-in-differences variables. The control variables *LnMarketcap*, *LnVolatility* and *LnTradingvolume* are the natural logarithms of respectively the market capitalization, the standard deviation of previous returns and trading volumes of the respective indices. Like the regression in the previous section, this regression is also executed with firm-specific fixed effects *FE*.

Because market capitalization seems to be a variable with explanatory power, I split the sample into subsamples based on market capitalization. Based on the thresholds used by Euronext, three subsamples are identified. The large cap segment contains stocks with a market capitalization above 1 billion, the mid cap segment contains stocks with a market capitalization between 150 million and 1 billion and the small cap segment contains stocks with a market capitalization below 150 million. I assigned every stock to the right sample and then executed the regression for each subsample separately. I did not only do this with the quoted bid ask spread as the dependent variable, but also with the stock price and abnormal return.

3.2.4. Coarsened exact matching

In the previous sections multiple methods, such as adding control variables and fixed effects, are applied to control for possible omitted variables. Besides omitted variables, the imposition of the short selling ban itself could also cause an endogeneity problem (Siciliano and Ventoruzzo, 2020). As mentioned before, Belgian regulators themselves chose to impose a short selling ban, so it was not introduced randomly. The decision made by the Belgian regulators to impose a short selling ban and the decision made by the dutch regulators not to impose one, could be influenced by the difference in performance and characteristics of Belgian and Dutch stocks.

To control for this possible problem, I use Coarsened exact matching in order to prepare a sample in which non-banned stocks are matched to banned stocks to control for endogenous selection on observed variables (Siciliano and Ventoruzzo, 2020). Matching is a method that can be used to improve the estimation of causal effects by decreasing imbalance in covariates between the treatment and control group (Blackwell et al., 2010). The goal is to delete observations from the data in order to improve the balance between the treatment and control group, which means that the distributions of the covariates are more similar in both groups.

There are many different matching techniques. Exact matching for example matches a treated observation to a control observation with the exact same covariate value (Greifer, 2023). The disadvantage of this technique is that it produces very few matches, hence the sample size decreases significantly. The Coarsened exact matching method uses an approach that produces a lot more matches, which is one of the main reasons I chose this method. The idea of Coarsened exact matching is to coarsen the data into groups based on one or more variables (Blackwell et al., 2010). These groups are called strata. Each observation is placed into the stratum that it belongs to based on the cutpoints in the matching variables. Each treated observation, in this case stock, is matched to the control stocks in the same stratum. It is not required that the number of treated observations has to be equal to the number of control observations within a stratum. This means that the treatment and control group are not necessarily of equal size after matching.

Following papers such as Le Moign and Spolaore (2022) and Siciliano and Ventoruzzo (2020) I chose market capitalization and industry as matching variables. For market capitalization I use the average market capitalization of stocks over the pre-ban period and I let the automatic binning algorithm of coarsened exact matching make the cutpoints. For industry I use the 4-digit SIC code and match on the first 2 numbers, so I set the cutpoints on 9.5 19.5 29.5 and so on. Based on these cutpoints, 18 strata are created and 10 are matched, which results in the below table. As can be observed in Table 7, 78 control stocks are matched to 80 treatment stocks. So, 8 control stocks and 1 treatment stock are unmatched. In total 762 observations are deleted, which means 5.46% of the sample is lost due to matching.

Table 7: The sample after applying Coarsened exact matching.

	Control	Treatment	Observations
All	86	81	13951
Matched	78	80	13189
Unmatched	8	1	762

As I use panel data, I calculated the average market capitalization for each stock in the pre-ban period in order to have 1 observation for every stock. In this cross-sectional setting coarsened exact matching is applied with average market capitalization and SIC code as matching variables. Then, the coarsened exact matching output, the weights, are merged with the panel data. To estimate the causal effect using this matched data, the weights are incorporated into the difference-in-differences regressions as described in the previous sections.

4. Results

4.1. Parallel trends assumption

As pointed out in Section 3.2.1, it is imported that the parallel trends assumption is not violated when using a difference-in-differences identification strategy. So, before executing the difference-in-differences regressions, the below hypothesis and alternative hypothesis are tested:

H_0: mean (control group) = mean (treatment group)

H_a: mean (control group) ≠ mean (treatment group)

The results of the two-sided t-tests for the trends over the pre-ban period for Price, Abnormal returns and Quoted bid-ask spread can be seen in respectively Table 8, 9 and 10. As can be seen in Table 8 the two-sided t-test gives a p-value of 0.865, which means the nul-hypothesis cannot be rejected when using a significance level of 5%. This means there is no evidence to assume that the average daily growth in price, the trend in price, differs between the treatment and control group in the pre-ban period. Which means the parallel trends assumption is not violated for the variable Price.

For the variables Abnormal returns and Quoted bid-ask spread the two sided t-test gives p-values of respectively 0.229 and 0.185. This means that for these 2 variables there is also no evidence that there is a difference in trend in the pre-ban period using a significance level of 5%. So, for all dependent variables that will be used in the regressions the parallel trends assumption is not violated, meaning that the data is suitable to use for difference-in-differences regressions.

Table 8: Results of the two-sided t-test for testing the parallel trends assumption for Price.

	Observations	Mean	Standard deviation
Price trend control group	42	-0.011	0.028
Price trend treatment group	42	-0.010	0.024

H_0: mean (Price trend control group) = mean (Price trend treatment group)
H_a: mean (Price trend control group) ≠ mean (Price trend treatment group)
Pr = 0.865

Table 9: Results of the two-sided t-test for testing the parallel trends assumption for Abnormal returns.

	Observations	Mean	Standard deviation
Abnormal returns trend control group	42	-0.158	5.044
Abnormal returns trend treatment group	42	-5.620	28.498

H_0: mean (Abnormal returns trend control group) = mean (Abnormal returns trend treatment group)
H_a: mean (Abnormal returns trend control group) ≠ mean (Abnormal returns trend treatment group)
Pr = 0.229

Table 10: Results of the two-sided t-test for testing the parallel trends assumption for Quoted Bid-Ask spreads.

	Observations	Mean	Standard deviation
Bid-ask trend control group	42	0.774	0.505
Bid-ask trend treatment group	42	0.625	0.453

H_0: mean (Bid-ask trend control group) = mean (Bid-ask trend treatment group)
H_a: mean (Bid-ask trend control group) ≠ mean (Bid-ask trend treatment group)
Pr = 0.185

4.2. Stock prices and Abnormal returns

In this section, I will describe the results for the first hypothesis: *There is a positive relationship between the enactment of a short selling ban and subsequent stock market returns and stock prices.* The results for this hypothesis are split into two parts, namely the relationship between the enactment of a short selling ban and stock prices and the relationship between the enactment of a short selling ban and returns.

First, I want to look at the relationship between the enactment of a short selling ban on stock prices. The results for the regressions to test this relationship are described in Table 11. As can be seen in the Table, the equation described in Section 3.2.2 is executed with all possible combinations of control variables. All regressions are executed with firm-specific fixed effects. As a result, the variable *ban* is omitted from the regressions, because of perfect collinearity with the fixed effects.

As can be seen in Table 11 in columns 2,3 and 4, all control variables are significantly associated with *LnPrice.* The first column reveals that the difference-in-differences estimators are significantly associated with *LnPrice.* However, if all control variables are added to the regression with the difference-in-differences estimators, the difference-in-differences estimators become insignificant as shown in column 8. The only significant variable in this column is *LnMarketcap*. The reason for this is that market capitalization is calculated by multiplying the stock price with the amount of shares outstanding. This means the stock price is on both sides of the regression, which is why *LnMarketcap* is left out of the regression and for interpretation the regression results in column 6 are used.

Column 6 shows a coefficient of 0.098 for the variable of interest *EventXBan,* which is significant on a 1% significance level. This means that stock prices increased by 1.10 ($e^{0.098)}$) or 10% for banned stocks (Belgian stocks) during the ban period compared to non-banned stocks (Dutch stocks). This suggests that the short selling ban supported stock prices, which is in line with the hypothesis. Furthermore, column 6 shows negative coefficients for the control variables *LnVolatility* and *LnTradingvolume*. This means that volatility and trading volume are negatively and significantly (at a significance level of 1%) associated with stock prices.

Table 11: The relationship between a short selling ban and stock prices.
In this table the results are shown for the execution of the regression equation in Section 3.2.2 with *LnPrice* as dependent variable, which is the natural logarithm of the stock price at the market close. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on the full sample with Belgian and Dutch stocks as described in Table 2. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

LnPrice	(1) Coefficient (t-value)	(2) Coefficient (t-value)	(3) Coefficient (t-value)	(4) Coefficient (t-value)	(5) Coefficient (t-value)	(6) Coefficient (t-value)	(7) Coefficient (t-value)	(8) Coefficient (t-value)
Event	-2.88***	-0.231***	-0.056	-0.241***	-0.052	-0.221***	-0.057	-0.055
	(-9.92)	(-8.59)	(-1.33)	(-8.16)	(-1.40)	(-7.89)	(-1.46)	(-1.47)
EventXBan	0.101***	0.091***	0.027	0.104***	0.027	0.098***	0.031	0.031
	(3.78)	(3.42)	(1.38)	(3.89)	(1.43)	(3.71)	(1.50)	(1.51)
LnVolatility		-0.086***			-0.016	-0.046***		-0.008
		(-17.88)			(-1.25)	(-11.42)		(-1.25)
LnMarketcap			0.849***		0.821***		0.805***	0.798***
			(6.98)		(5.93)		(5.52)	(5.32)
LnTradingvolume				-0.151***		-0.115***	-0.035	-0.30
				(-17.24)		(-11.06)	(-1.32)	(-1.34)
Constant	3.25***	2.881***	-8.562***	3.870***	-8.251***	3.523***	-7.804***	-7.766***
	(338.46)	(141.07)	(-5.06)	(103.18)	(-4.41	(70.18)	(-3.64)	(-3.61)
Observations	13951	13951	13951	13951	13951	13951	13951	13951
Adj. R-squared	0.018	0.046	0.224	0.060	0.226	0.068	0.229	0.229
F-value	81.35***	141.01***	229.25***	148.20***	395.24***	119.95***	319.09***	229.48***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

To test the second part of the first hypothesis I investigate the relationship between the enactment of a short selling ban and abnormal returns. The results for the regressions to test this relationship are described in Table 12. As can be seen in the Table, the equation described in Section 3.2.2 is now executed with *LnAbnormalreturn* as the dependent variable, and all possible combinations of control variables. All regressions are again executed with firm-specific fixed effects, which means the variable *ban* is omitted from the regressions because of collinearity.

As can be seen in the first column of Table 12, The regression with only the difference-in-differences estimators gives a negative and significant coefficient for the variable of interest *EventXBan* at the 1% level. Column 8 shows that the coefficient of *EventXBan* stays significant at the 5% and 10% level, but not at the 1% level when all control variables are added. Column 8 also shows that all variables are significant except for *LnVolatility.* Column 7 shows that leaving this variable out does not change the coefficients and significance of the other variables much. For this reason I used the regression results in column 7 for the interpretation of the coefficients.

For the control variables *LnMarketcap* and *LnTradingvolume,* Column 7 shows positive and significant coefficients at respectively the 1% and 5% significance level. This means that for both control variables there is a positive and significant relationship with abnormal returns. This positive relationship for *LnTradingvolume* is in line with Pathirawasam (2011). The positive coefficient of *LnMarketcap* means that higher market capitalization is associated with higher abnormal returns.

As can be seen in column 7, the variable of interest *EventXBan* has a coefficient of -0.006, which is significant at a significance level of 5%. This result indicates that the enactment of the short selling ban is linked with a decrease in abnormal returns of 1% ($e^{(-0.006)}$) for banned stocks during the ban period compared to non-banned stocks, meaning that the non-banned stocks outperformed the banned stocks. This result is not in line with the hypothesis, but it is in line with some of the discussed literature in the Literature review such as Le Moign and Spolaore (2022) and Siciliano and Ventoruzzo (2020) who also use the abnormal returns as the dependent variable.

The results for abnormal returns contradict the results for stock price as described before. Based on the results in Table 11 and 12 one would conclude that the short selling ban supports stock prices, but it does not support abnormal returns. The performance of the market index of both countries probably plays a big role in this as the abnormal return of a stock is measured as the return in excess of the return on the market index. So, based on the results for stock price one cannot reject the Hypothesis 1, but based on the results for abnormal returns one would have to reject the hypothesis. It is thus important which measure for performance one uses to investigate the influence of a short selling ban on stock performance.

Table 12: The relationship between a short selling ban and abnormal returns.

In this table the results are shown for the execution of the regression equation in Section 3.2.2 with *LnAbnormalreturn* as dependent variable, which is the natural logarithm of the return in excess of the return on the respective index. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on the full sample with Belgian and Dutch stocks as described in Table 2. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

LnAbnormalreturn	(1) Coefficient (t-value)	(2) Coefficient (t-value)	(3) Coefficient (t-value)	(4) Coefficient (t-value)	(5) Coefficient (t-value)	(6) Coefficient (t-value)	(7) Coefficient (t-value)	(8) Coefficient (t-value)
Event	0.001	0.002*	0.008**	0.001	0.008**	0.002	0.008**	0.008**
	(0.80)	(1.81)	(2.29)	(0.91)	(2.34)	(1.67)	(2.11)	(2.24)
EventXBan	-0.004***	-0.004***	-0.006**	-0.004***	-0.006**	-0.004***	-0.006**	-0.006**
	(-3.44)	(-3.74)	(-2.69)	(-3.43)	(-2.63)	(-3.82)	(-2.50)	(-2.56)
LnVolatility		-0.002***			0.001	-0.002***		-0.001
		(-3.07)			(0.55)	(-3.51)		(-0.60)
LnMarketcap			0.027***		0.028***		0.032***	0.031***
			(3.58)		(3.05)		(3.13)	(2.95)
LnTradingvolume				-0.001		0.001	0.004**	0.004**
				(-0.85)		(0.82)	(1.99)	(2.59)
Constant	-0.000	-0.008***	-0.375***	0.003	-0.387***	-0.012**	-0.456***	-0.453***
	(-0.04)	(-2.93	(-3.56)	(0.88)	(-3.12)	(-2.32)	(-3.09)	(-3.03)
Observations	13951	13951	13951	13951	13951	13951	13951	13951
Adj. R-squared	0.001	0.001	0.001	0.000	0.001	0.000	0.001	0.001
F-value	9.34***	12.36***	15.21***	7.82***	22.55***	9.39***	13.89***	18.79***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

4.3. Liquidity

In this section, I will describe the results for the second hypothesis: *There is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market.* The results of the regressions that were used to test this relationship are described in Table 13. As can be seen in the Table, the equation described in Section 3.2.3 is executed with all possible combinations of control variables. All regressions are executed with firm-specific fixed effects. As a result, the variable *ban* is omitted from the regressions, because of perfect collinearity with the fixed effects.

As can be seen in Table 13 in columns 2,3 and 4, all control variables are significantly associated with *Ln_Q_Bid_Ask.* The first column shows that the variable of interest *EventXBan* has an insignificant coefficient. If all control variables are added to the regression with the difference-in-differences estimators, all variables are significant except for the variable of interest *EventXBan* as is shown in column 8. As a result, this variable cannot be interpreted.

Column 8 also reveals a significant coefficient for *LnVolatility,* which is in line with the relationship between volatility and bid-ask spreads as described by Siciliano and Ventoruzzo (2020). The negative and significant coefficient of *LnMarketcap* as shown in column 8 means that higher market capitalization is associated with lower bid-ask spreads. The positive and significant coefficient of *LnTradingvolume* as revealed in column 8, confirms the theory of Beber and Pagano (2013) that higher trading volumes can be associated with wider bid-ask spreads during periods of uncertainty in the stock market. The variable *Event* has a positive coefficient of 0.294, which is significant at a 1% significance level. This means that for the entire sample of stocks, the short selling ban is linked with an increase in quoted bid-ask spreads of 34% ($e^{0.294}$), there is just no significant difference between banned and non-banned stocks in this increase. This is in line with the descriptive statistics as described in Tables 3 to 6, as the average increase in bid-ask spreads for both countries are comparable.

As a result of the aforementioned results, the hypothesis that there is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market, can be rejected. This is in line with Benhami, van Veldhuizen and Schoolderman (2022) as they also find comparable differences in bid-ask spreads between the treatment and control group in pre-ban period and the ban period. But, this is not in line with most of the discussed literature such as Le Moign and Spolaore (2022), Beber and Pagano (2013) and Siciliano and Ventoruzzo (2020).

A reason for the different result might be the fact that the short selling ban was imposed during a time that was already turbulent, because of COVID-19. At the time, bid-ask spreads were already abnormally high for both stocks that were targeted by the short selling ban and stocks that were not targeted (Beber and Pagano, 2013). Another reason might be that the Netherlands and Belgium are comparable in terms of regulation with respect to short selling. Both countries already had a ban on naked short selling before the short selling ban was enacted, so the only difference was that a ban on conventional short selling was added for Belgian stocks.

Table 13: The relationship between a short selling ban and liquidity.
In this table the results are shown for the execution of the regression equation in Section 3.2.3 with *Ln_Q_Bid_Ask* as dependent variable, which is the natural logarithm of the quoted bid-ask spread. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on the full sample with Belgian and Dutch stocks as described in Table 2. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

Ln_Q_Bid_Ask	(1) Coefficient (t-value)	(2) Coefficient (t-value)	(3) Coefficient (t-value)	(4) Coefficient (t-value)	(5) Coefficient (t-value)	(6) Coefficient (t-value)	(7) Coefficient (t-value)	(8) Coefficient (t-value)
Event	0.462***	0.359***	0.309***	0.388***	0.283***	0.346***	0.314***	0.294***
	(13.44)	(12.59)	(8.65)	(11.87)	(9.23)	(11.67)	(9.38)	(9.15)
EventXBan	0.008	0.026	0.057	0.003	0.053	0.017	0.032	0.038
	(0.16)	(0.59)	(1.42)	(0.07)	(1.32)	(0.37)	(0.77)	(0.90)
LnVolatility		0.154***			0.124***	0.100***		0.088***
		(8.03)			(6.61)	(5.37)		(4.71)
LnMarketcap			-0.558***		-0.350***		-0.323***	-0.248***
			(-6.50)		(-6.51)		(-5.30)	(-4.08)
LnTradingvolume				0.235***		0.156***	0.189***	0.130***
				(9.26)		(7.27)	(7.78)	(5.95)
Constant	-5.740***	-5.088***	2.021*	-6.711***	-0.341	-5.961***	-2.031**	-2.449***
	(-332.87)	(-60.27)	(1.69)	(-63.16)	(-0.45)	(-45.97)	(-2.37)	(-2.80)
Observations	13951	13951	13951	13951	13951	13951	13951	13951
Adj. R-squared	0.022	0.016	0.091	0.004	0.099	0.006	0.099	0.103
F-value	99.14***	95.62***	86.06***	85.63***	78.46***	73.54***	77.52***	69.14***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

4.4 Effects by size

Even when no short selling restrictions are in place, market makers are reluctant to provide liquidity for small-cap stocks, causing wider bid-ask spreads (Beber and Pagano, 2013). As can be seen in Table 13 higher market capitalization seems indeed to be negatively associated with quoted bid-ask spreads. I split the sample into a large-cap, mid-cap and small-cap sample based on the size thresholds used by Euronext. In order to assess the difference in effects of a short selling ban on the liquidity of stocks with different market capitalization, I executed the regression equation as described in section 3.2.3 for each size sample separately. The same was done for Price and Abnormal returns as can be seen in Tables 15 and 16. For these two variables I used the equations which were used for the interpretations in Section 4.2.

For the entire sample, the short selling ban did not cause a difference in quoted bid-ask spreads between the treatment and control group during the ban period as was shown in Table 13. If one only looks at the large cap sample of stocks, Table 14 shows a coefficient of 0.105 for *EventXBan,* which is significant at a significance level of 5%. This means that for large cap stocks, quoted bid-ask spreads increased by 11% ($e^{0.105}$) during the ban period for banned stocks, compared to the control group. As increased bid-ask spreads mean a decrease in liquidity, this result is in line with the second hypothesis which states: *There is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market.* No inferences can be made based on the regression results for the mid-cap and small-cap sample, because *EventXBan* has an insignificant coefficient in both cases.

As can be seen in Table 15, *EventXBan* has a positive and significant (at the 5% level) coefficient for both the large-cap and mid-cap sample. Table 15 shows that the coefficient for the mid-cap sample is higher than for the large-cap sample. This means that the short selling ban supports prices more for mid-cap stocks than for large cap stocks, namely 11.85% versus 10.63%. For small-cap stocks, the coefficient cannot be interpreted as it is insignificant.

As can be seen in Table 16, *EventXBan* has a negative and significant coefficient for both the large-cap and mid-cap sample. The coefficient for *EventXBan* for the mid-cap sample can only be interpreted, keeping in mind that it is only significant at a 1% significance level. Table 16 reveals that the coefficient for the large-cap sample is lower than for the mid-cap sample. This means that the short selling ban had a bigger negative impact on large-cap stocks compared to mid-cap stocks, namely -0.7% versus -0.5%. For small-cap stocks, the coefficient cannot be interpreted as it is insignificant. A reason for the insignificance of the coefficients for the small-cap sample could be the small size of the sample in terms of number of stocks compared to the large-cap and mid-cap samples.

Table 14: The relationship between a short selling ban and liquidity by size

In this table the results are shown for the execution of the regression equation in Section 3.2.3 with *Ln_Q_Bid_Ask* as dependent variable, which is the natural logarithm of the quoted bid-ask spread. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are seperately executed on a large- mid- and small-cap sample of Belgian and Dutch stocks. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

Ln_Q_Bid_Ask	Large Coefficient (t-value)	Mid Coefficient (t-value)	Small Coefficient (t-value)
Event	0.336***	0.248***	0.162*
	(8.19)	(4.09)	(1.78)
EventXBan	0.105**	0.035	-0.225
	(2.46)	(0.51)	(-1.69)
LnVolatility	0.053**	0.122***	0.108**
	(2.57)	(5.63)	(2.50)
LnMarketcap	-0.221**	-0.273***	-0.601*
	(-2.32)	(-4.94)	(-1.85)
LnTradingvolume	0.044*	0.128***	0.471***
	(1.72)	(4.89)	(8.53)
Constant	-3.200**	-1.565**	0.902
	(-2.16)	(-2.23)	(0.26)
Observations	7049	5106	1790
Adj. R-squared	0.239	0.118	0.165
F-value	35.20***	78.48***	43.36***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

Table 15: The relationship between a short selling ban and stock prices by size

In this table the results are shown for the execution of the regression equation in Section 3.2.2 with *LnPrice* as dependent variable, which is the natural logarithm of the stock price at the market close. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are seperately executed on a large- mid- and small-cap sample of Belgian and Dutch stocks.. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

LnPrice	Large Coefficient (t-value)	Mid Coefficient (t-value)	Small Coefficient (t-value)
Event	-0.193***	-0.259***	-0.222***
	(-5.66)	(-5.44)	(-8.19)
EventXBan	0.101**	0.112**	0.058
	(2.73)	(2.81)	(0.65)
LnVolatility	-0.065***	-0.044***	-0.012*
	(-7.31)	(-7.53)	(-1.77)
LnTradingvolume	-0.109***	-0.113***	-0.116***
	(-10.17)	(-7.21)	(-6.95)
Constant	3.928***	3.231***	2.508***
	(60.73)	(40.69)	(30.60)
Observations	7049	5106	1790
Adj. R-squared	0.066	0.089	0.052
F-value	64.10***	110.02***	25.31***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

Table 16: The relationship between a short selling ban and abnormal returns by size

In this table the results are shown for the execution of the regression equation in Section 3.2.2 with *LnAbnormalreturns* as independent variable, which is the natural logarithm of the return in excess of the return on the respective index. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are seperately executed on a large- mid- and small-cap sample of Belgian and Dutch stocks.. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level

LnAbnormal_return	Large Coefficient (t-value)	Mid Coefficient (t-value)	Small Coefficient (t-value)
Event	0.007**	0.006	0.022*
	(2.54)	(1.67)	(2.07)
EventXBan	-0.007***	-0.005*	-0.012
	(-2.95)	(-1.84)	(-0.99)
LnMarketcap	0.029***	0.022*	0.098**
	(5.36)	(2.03)	(2.24)
LnTradingvolume	0.004***	0.002	0.011*
	(3.34)	(0.78)	(1.75)
Constant	-0.457***	-0.288*	-1.110**
	(-5.37)	(-1.96)	(-2.22)
Observations	7049	5109	1793
Adj. R-squared	0.001	0.001	0.001
F-value	15.46***	5.61***	1.64

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

4.5 Results with Coarsened exact matching

As explained in Section 3.2.4, the enactment of the short selling ban could be an endogenous decision made by Belgian regulators. It is likely that this ban was not introduced at random. This means that the relation between the imposition of a short selling ban and market liquidity and returns, might run in the opposite direction as well, meaning that a short selling ban was imposed because of bad market liquidity and returns (Siciliano and Ventoruzzo, 2020). To control for this possible problem, the regressions executed in Sections 4.2 and 4.3 are executed on a matched sample of stocks as explained in Section 3.2.4

The results of the regressions that were used for the interpretation in Sections 4.2 and 4.3 are tabulated in Table 17. If one compares the coefficients in Table 17 for the regression on *Lnprice* with the coefficients for the same regression in Table 11 column 6, only small differences can be spotted. The coefficient for the variable of interest *EventXBan* is even the same and is still significant at a 1% significance level. So, for *LnPrice,* it can be concluded that the results of Table 11 column 6 also hold after applying Coarsened exact matching.

If one compares the coefficients in Table 17 for the regression on *LnAbnormalreturn* with the coefficients for the same regression in Table 12 column 7, there are some differences in the coefficients. The coefficient for the variable of interest *EventXBan* is smaller for the regression on the matched sample than for the unmatched sample. This means that that there is a more negative association between the imposition of the short selling ban and abnormal returns for the matched sample compared to the unmatched sample, namely -0.8% versus -0.6%. Both results are significant at a significance level of 1%, so it can be concluded that the results of Table 12 column 7 also hold after applying Coarsened exact matching.

If one compares the coefficients in Table 17 for the regression on Ln_Q_Bid_Ask with the coefficients for the same regression in Table 13 column 8, it can be observed that the regression on the matched sample gives similar results in terms of significance. In Table 17, the coefficients for all variables are significant except for the variable of interest *EventXBan.* So, just as with the unmatched sample, the coefficient of *EventXBan* cannot be interpreted for the matched sample. It can thus be concluded that after applying Coarsened exact matching, the second hypothesis is still rejected.

Table 17: Results after applying Coarsened exact matching
In this table the results are shown for the execution of the regression equations in Sections 3.2.2 and 3.2.3 with *LnPrice*, *LnAbnormalreturns* and *Ln_Q_Bid_Ask* as dependent variables. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on a matched sample with Belgian and Dutch stocks as described in Table 7. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

Matching	*LnPrice* Coefficient (t-value)	*LnAbnormal returns* Coefficient (t-value)	Ln_Q_Bid_ask Coefficient (t-value)
Event	-0.221***	0.011**	0.344***
	(-6.85)	(2.40)	(7.74)
EventXBan	0.098***	-0.008***	-0.017
	(3.53)	(-2.78)	(-0.47)
LnVolatility	-0.043***		0.111***
	(-10.68)		(7.65)
LnMarketcap		0.042***	-0.203**
		(4.50)	(-2.46)
LnTradingvolume	-0.114***	0.006***	0.139***
	(-10.57)	(5.56)	(6.14)
Constant	3.443***	-0.604***	-2.919**
	(65.31)	(-4.58)	(-2.43)
Observations	13189	13189	13189
Adj. R-squared	0.085	0.001	0.119
F-value	114.16***	15.06***	91.22***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

4.6 Robustness checks

To test the robustness of the results, several robustness checks were performed in the previous sections. In Sections 4.2 and 4.3 the regression equation was executed with all possible combinations of controls. For the regressions on the dependent variable *LnPrice*, the coefficient of the variable of interest *EventXBan* remained positive after adding different combinations of control variables. However, the coefficient was only significant when leaving out the variable *LnMarketcap.* For the regressions with *LnAbnormalreturn* as dependent variable, the coefficient of *EventXBan* remained negative and significant at the 1% level with all possible combinations of control variables. For the regressions with *Ln_Q_Bid_Ask* as dependent variable the coefficient of *EventXBan* was insignificant with all possible combinations of controls.

Besides control variables, I also added firm-specific fixed effects to all regressions. I also executed the regressions with industry fixed effects using the first two digits of a firm's SIC industry code, to see if this would give different results. Appendix A Table 1 shows the regression results for the regression equations used for the interpretation in Sections 4.2 and 4.3, with industry fixed effects. If one compares Appendix A Table 1 in the appendix with the Tables in Sections 4.2 and 4.3, it can be seen that the clustering of standard errors at the industry level does not change much to the significance of the coefficients.

At the end of Section 2.2, it was mentioned that the supervisory authority in Belgium initially imposed a one-day short selling ban on 17 stocks that trade on the Euronext Brussels on the 16th of March 2020 and one day later they decided to make It an exchange-wide short selling ban. So, some stocks in the sample were already affected by the short selling ban on the 16th of March. I amended the variable of interest *EventXBan* in a way that the 16th of March is the start of the ban period and executed the regression equations used in Sections 4.2 and 4.3 with the amended difference-in-differences estimators. The results for these regressions are tabulated in Appendix A Table 2. Comparing the regression results of Appendix A Table 2 with the results of the same regressions in Table 11,12 and 13, it can be seen that there are only small differences in the variables coefficients and their significance. It can thus be concluded that the results hold when including the day on which the initial ban was imposed.

4.7 Endogeneity

When investigating the causal effect of a short selling ban on market quality and performance, several endogeneity problems can occur. In the previous sections of this paper, I tried to solve for some of the endogeneity problems. However, some endogeneity problems might be unsolved for. I will also discuss those possible problems in this section.

In Section 4.5 I explained that the enactment of the short selling ban could be an endogenous decision made by Belgian regulators and that this might mean that the relationship between the imposition of a short selling ban and market quality, runs in the opposite direction as well. I tried to solve for this simultaneity problem by applying Coarsened exact matching and executing the regressions on a matched sample of stocks. Section 4.5 shows that the results hold after applying coarsened exact matching.

The decision to impose a short selling ban was based on economic developments, as is it was a reaction to the market crash in 2020 (Matthews et al., 2021). I selected a sample of Belgian stocks, because Belgium imposed an exchange wide short selling ban. This could cause a selection bias as the short selling ban targeted stocks that were already performing bad, because of economic developments. For convenience I only chose one country for the treatment group, because this way one does not need to control for differences in regulation and different kinds of short selling bans between countries. However, to solve for selection bias it might be better to use multiple countries for the treatment group with differences in short selling bans and regulation. On the other hand, the fact that the Netherlands was also affected by the same market crash as Belgium and the similarity in regulation between both countries make the data less vulnerable to selection bias.

In the previous Sections I tried to solve for omitted variables bias in multiple ways. By adding control variables I controlled for volatility, trading volume and market capitalization. By adding stock-specific fixed effects and applying matching I controlled for other industry and stock characteristics. Despite these efforts, the data might still be prone to other omitted variables I did not succeed to control for. For example I did not control for regulation and measures that were imposed to fight the spread of the COVID-19 virus. As explained before, these measures had a huge impact on the economy and indirectly on the stock market. To control for this, one would have to come up with a variable that filters out the effect that measures imposed by both countries had on the stock market.

The last endogeneity problem I had to deal with is the measurement problem. Especially for the control variables this could be a problem. The variable *LnVolatility,* is measured as the natural logarithm of the rolling standard deviation of the returns of a stock based on the previous 5 trading days. The values of *LnVolatility* depend on how it was calculated and differs from the real volatility, this difference is the measurement error. For the variable *LnTradingvolume,* there is a similar problem. For this variable I used the trading volume on the main index of the respective country. Obviously, there is a difference between this trading volume and the trading volume for each individual stock. The setting used in Section 4.5 controlled for a part of this problem as Coarsened exact matching is approximately invariant to measurement error (Blackwell et al., 2010).

5. Conclusion

In this paper, I tried to answer the question: *What are the effects of a short selling ban on the stock market?* I did this by testing two hypotheses. The first hypothesis that was tested is: *There is a positive relationship between the enactment of a short selling ban and subsequent stock market returns and stock prices.* I tested this hypothesis by testing the relationship between the enactment of a short selling ban and subsequent stock prices and abnormal returns. After controlling for several control variables and applying different methods, I found a positive and significant relationship between the enactment of a short selling ban and stock prices. For abnormal returns I found a negative and significant relationship between the enactment of a short selling ban and abnormal returns. It thus depends on the measure of performance one chooses whether it is concluded that the first hypothesis is rejected or not. For stock price, Hypothesis 1 cannot be rejected, for abnormal return Hypothesis 1 can be rejected.

The second hypothesis that was tested is: *There is a negative relationship between the enactment of a short selling ban and subsequent liquidity in the stock market.* To test this hypothesis I investigated the relationship between the enactment of a short selling ban and subsequent quoted bid-ask spreads. After controlling for several control variables and applying different methods, I did not find a significant relationship between the enactment of a short selling ban and stock prices. An exception can however be made for the large cap stocks, as a positive relationship was found between the enactment of a short selling ban and quoted bid-ask spread for this sample of stocks. To conclude, for large cap stocks Hypothesis 1 cannot be rejected, but for the entire sample of stocks, Hypothesis 1 can be rejected.

Using the aforementioned results several statements can be made regarding the research question: *What are the effects of a short selling ban on the stock market?* It was found that the enactment of a short selling ban supports stock prices. However, it was also found that the enactment of a short selling ban is related with an underperformance of banned stocks in terms of abnormal returns. It is thus important which measure of performance one uses when investigating the effect of a short selling ban. It was also found that there is no significant relationship between the enactment of a short selling ban and liquidity, when using a variety of stocks in terms of size. For large-cap stocks, it was found that the enactment of a short selling ban is associated with a decrease in liquidity.

The research done in this paper has several shortcomings. Some of them were already covered in Sections 4.6 and 4.7. The most important one is that I did not control for regulation and measures that were imposed to fight the spread of the COVID-19 virus. These measures were partly responsible for the market crash on which the short selling ban was a reaction to, so this could have an impact on the results. So, for future research it might be useful to come up with a variable that can serve as a proxy for COVID-19 measures imposed by both countries.

In Section 4.5 I described that there is a likely possibility that the relationship between the imposition of a short selling ban and market quality runs in the opposite direction as well. For future research, it might be interesting to find out if it is possible to solve for this simultaneity problem in a better way, by for example applying an instrumental variables method, which is a good way to solve for simultaneity (Heckman, 1996).

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Appendix A Robustness checks

Table 1: Results with industry fixed effects

In this table the results are shown for the execution of the regression equations in Sections 3.2.2 and 3.2.3 with *LnPrice*, *LnAbnormalreturns* and *Ln_Q_Bid_Ask* as dependent variables. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on the full sample with Belgian and Dutch stocks as described in Table 2. Each regression is estimated using OLS on daily data with robust standard errors clustered at the industry level.

SIC	LnPrice Coefficient (t-value)	LnAbnormal return Coefficient (t-value)	Ln_Q_Bid_Ask Coefficient (t-value)
Event	-0.221***	0.008**	0.294***
	(-10.52)	(3.11)	(9.05)
EventXBan	0.098***	-0.006**	0.038
	(3.65)	(-3.34)	(0.83)
LnVolatility	-0.046***		0.088***
	(-9.51)		(5.88)
LnMarketcap		0.032***	-0.248***
		(3.91)	(-3.89)
LnTradingvolume	-0.115***	0.004**	0.130***
	(-18.27)	(2.58)	(5.73)
Constant	3.523***	-0.456***	-2.449***
	(89.98)	(-3.86)	(-2.79)
Observations	13951	13951	13951
Adj. R-squared	0.068	0.001	0.103
F-value	163.27***	10.38***	117.63***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%

Table 2: Results with Short selling ban enactment on the 16th of March

In this table the results are shown for the execution of the regression equations in Sections 3.2.2 and 3.2.3 with *LnPrice*, *LnAbnormalreturns* and *Ln_Q_Bid_Ask* as dependent variables. *Event* and *EventXBan* are the difference-in-differences estimators and *EventXBan* is the variable of interest. *LnVolatility* is the natural logarithm of the 5 days rolling standard deviation of returns. *LnMarketcap* is the natural logarithm of market capitalization. *LnTradingvolume* is the natural logarithm of the trading volume on the index of the respective country. The regressions are executed on the full sample with Belgian and Dutch stocks as described in Table 2. Each regression is estimated using OLS on daily data with robust standard errors clustered at the stock level.

	LnPrice Coefficient (t-value)	*LnAbnormal return* Coefficient (t-value)	*Ln_Q_Bid_Ask* Coefficient (t-value)
Event	-0.23***	0.007**	0.319***
	(-7.95)	(2.07)	(9.55)
EventXBan	0.099***	-0.006**	0.033
	(3.67)	(-2.41)	(0.77)
LnVolatility	-0.042***		0.082***
	(-10.53)		(4.30)
LnMarketcap		0.030***	-0.209***
		(3.32)	(-3.21)
LnTradingvolume	-0.110***	0.004**	0.124***
	(-10.49)	(2.07)	(5.55)
Constant	3.525***	-0.430***	-2.999***
	(69.80)	(-3.26)	(-3.22)
Observations	13951	13951	13951
Adj. R-squared	0.065	0.001	0.105
F-value	124.87***	11.08***	70.96***

*Significant on a significance level of 10% ** Significant on a significance level of 5% *** Significant on a significance level of 1%