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What is it good for, absolutely nothing?

The European short-selling restriction and the effects on volatility during the Covid-19 pandemic

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Thesis Summary

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Authors	Albin Eriksson & Henrik Bolle
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Keywords	Short-selling restriction, Covid-19, Volatility, Difference-in-Difference estimator
Purpose	Our aim is to study if the stated reason for the implementation of the short-selling restrictions by regulators during the Covid-19 crisis actually achieved a decrease in volatility.
Methodology	The quantitative methodological approach utilizes a Difference-in-Difference estimator for three different approaches. We conduct both a base regression and a modified regression including three different specifications each.
Theoretical Perspectives	This study has its theoretical foundation in the role of short-sellers in equity markets. With the aim to investigate the effect that restricting short-selling have on volatility
Empirical Foundation	The sample consists of stock and index data from six European countries divided into a treatment and a control group. The time period of interest is the 18th of September 2019 until the 18th of May 2020.
Conclusions	All three approaches exhibited analogous results regarding the short-selling restrictions impact on volatility since the δ-variable that represents the restriction effect, was a positive coefficient. Moreover, the δ-variable was significant in all base models and in all modified regressions, except for the Index approach. Implying that the implementation of the short-selling restriction increased market volatility. Hence, in line with previous studies, we argue that an implementation of short-selling restrictions is not recommended if the stated purpose of it refers to a reduction of volatility. Moreover, our findings indicate that other financial government interactions rather than just short-selling restrictions are affecting market volatility.

Abstract

The aim of this study is to examine if the stated reason for the implementation of the short-selling restrictions by regulators during the Covid-19 crisis actually achieved a decrease in volatility. This study has its theoretical foundation in the role of short-sellers in equity markets. With the aim to investigate the effect that restricting short-selling have on volatility. The sample consists of stock and index data from six European countries. The time period of interest is the 18th of September 2019 until the 18th of May 2020. This way there is a pre- and post-restriction period whereas a Difference-in-Difference estimator is applicable. The quantitative methodological design includes three different approaches. Whereas, one is examining the volatility on an index-level. The second one, is a decomposed index approach where we include all individual stocks on each major index. Finally, in the third one we solely examine the stocks in the financial sector. We conclude that all three approaches exhibit analogous results, since the δ-variable that represents the restriction effect, is a positive coefficient. Moreover, the δ-variable is significant in all base models and in all modified regressions, except for the index approach. This implies, that the implementation of the short-selling restriction increased market volatility. Hence, in line with previous studies, we argue that an implementation of short-selling restrictions is not recommended if the stated purpose of it refers to a reduction of volatility. Moreover, our findings indicate that other financial government interactions rather than just short-selling restrictions are affecting market volatility.

Keywords: Short-selling restriction, Covid-19, Volatility, Difference-in-Difference estimator

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1 Introduction

In the following chapter the subject of the study and its background is presented. Further, the problem discussion is introduced and from it follows the purpose of the study, delimitations and finally the research question of the study.

During the COVID-19 pandemic in 2020, the most impactful pandemic since the 1918-1920 Spanish flu, there was a major decline in demand and supply worldwide leading to large economic uncertainty. As a result, stock prices also fell worldwide and in March 2020 stock markets were down 25% from where they were in January. According to Siciliano and Ventoruzzo (2020) this represents one of the most brutal and fastest declines in a century. Naturally, the volatility was also high following this abrupt decline. As can be seen from the implied volatility, measured on EURO STOXX 50 Index options, the VSTOXX closed at 86% on the 16th of March 2020 reflecting the second highest close ever (Qontigo, n.d.). This in turn, led several regulators across Europe to impose short-selling restrictions in an attempt to stop downward speculative pressure on the equity markets and trying to stabilize the confidence of investors.

Short-selling restrictions have been imposed historically as well, for example during the financial crisis in 2008 and during the Eurozone crisis in the aftermath of the financial crisis. The difference this time was that it was not a united action in Europe but rather an individual country decision. On the 18th of March 2020 six European countries, namely France, Austria, Italy, Spain, Greece and Belgium, imposed a temporary short-selling restriction. The restriction prohibited investors from engaging in short selling and transactions that could constitute or increase net short positions on stocks (Siciliano & Ventoruzzo, 2020). Further, the fact that it was only lasting for two months, there were no signs of a banking crisis or systematic risk as in earlier cases, e.g., during the financial crisis in 2008, and that it included all stocks indiscriminately made this ban unique (Bessler & Vendrasco, 2020). Contrarily, the United States did not impose a short-selling restriction as they have done historically during major crises. The Securities and Exchange Commission Chairman (SEC) chairman Jay Clayton stated that the reason for it was that in order to facilitate ordinary market trading investors have to be able to be on the short-side of the market (Kiernan, 2020). Perhaps another reason for the decision is based on that the effects of such restrictions have been and are still being examined thoroughly and that the costs actually appear to outweigh the benefits. In addition, Beber and Pagano (2013) summarized their study of the effects during the financial crisis with a quote of the former SEC Chairman Christopher Cox "Knowing what we know now, ... [we] would not do it again. The costs appear to outweigh the benefits." and stating that they hope that this lesson is learned for future crises.

When implementing restrictions or bans regulators often refer to low volatility as a justification. Although, the majority of previous literature on the subject argue that the effects are actually the opposite (e.g., Alves, Mendes & Silva, 2016; Beber, Fabbri, Pagano & Simonelli, 2020; Beber & Pagano, 2013; Bessler & Vendrasco, 2020; Boehmer, Jones & Zhang, 2013; Bohl, Reher & Wilfling, 2016; Helmes, Henker & Henker, 2017; Siciliano & Ventoruzzo, 2020). Further, as recently stated in a paper by Bessler and Vendrasco (2020), once again, a vast majority of the previous literature on this subject does not recommend implementations of short-selling restrictions as they negatively affect market quality, i.e., liquidity, volatility and price discovery mechanisms, even in times of crisis. Thus, according to the paper it is seen as surprising that some European countries introduced restrictions during the COVID-19 crisis and that investigating the outcomes are of major importance. Furthermore, Alves, Mendes and Silva (2016) point out that the effects of short-selling bans are occasional and therefore each restriction deserves to be studied. In addition, they also argue that studies done on European Union markets warrants special attention since there is scarce empirical evidence on the impact of short-selling restrictions on this market compared to the United States. Finally, there seems to be somewhat of a consensus on the loss in market quality after a restriction has been imposed regardless of crisis. However, much less consideration has been given to investigate whether the stated goals by regulators when imposing the restrictions has been met or not (Helmes, Henker & Henker, 2017). Therefore, in this paper we focus on addressing both of these gaps in the literature by examining the effects of the short-selling restrictions on the contribution to a calming of the market for European countries during the Covid-19 pandemic crisis. In other words, if the short-selling restrictions led to a reduced volatility on the selected stocks during this pandemic crisis. This is made possible due to the fact that different government interventions were implemented, one of them being short-selling restrictions. In order to, combat the volatility caused by the Covid-19 pandemic, which acts as a natural experiment since it is an exogenous shock (Siciliano & Ventoruzzo, 2020).

An understanding of the effects of short-selling restrictions imposed by market regulators during turbulent times are of extreme importance for both the regulators themselves and investors. Our aim is therefore, to study if the stated reason for the implementation of the short-selling restrictions by regulators on the 18th of March 2020 during the Covid-19 crisis actually achieved a decrease in volatility on the banned stocks. Out of the six countries that implemented restrictions, Austria, Belgium and France are included in the treatment group and three other countries are included as a control group. Namely, Germany, the Netherlands and Sweden. In order to make the two groups similar and thus comparable they are selected based on a set of parameters. That is, credit metrics, regulatory characteristics and similar industries. The time period of interest is the 18th of September 2019 until the 18th of May 2020, of which the period from the 18th of March 2020 represents the restriction period. This way we have a pre- and post-restriction period. Thus, we are able to examine the short-selling restrictions effect on volatility by applying a Difference-in-Difference estimator. Three different approaches are applied. Whereas, one is examining the volatility on an index-level, where also a synthetic control group is created for robustness. The second one, is a decomposed index approach where we include all individual stocks on each major index. Finally, in the third one we solely examine the stocks in the financial sector. In order to do this, we examine the following research hypothesis:

The short-selling restrictions during the Covid-19 pandemic did not have an impact on the reduction of volatility

By doing so, we find that for all three approaches the δ-variable that represents the restriction effect, is a positive coefficient. Moreover, the δ-variable is significant in all base models and in all modified regressions, except for the index approach. The short-selling restriction increased market volatility in a range of between 0.06 and 0.37% on a daily basis and 0.74 to 2.79% on a monthly basis, depending on the model and specification. Furthermore, our findings indicate that other financial government interactions rather than just short-selling restrictions are affecting market volatility. We believe that this study is of value for academia and especially for future research of impact of short-selling restrictions implemented by regulators during a crisis. Specifically, due to the scarce empirical evidence on European Union markets and the lack of research focusing on if the stated goals by regulators when imposing restrictions has been fulfilled.

The rest of this paper is structured as follows: section 2 is a description of the theoretical framework that laid the foundation of this paper and a summary of previous literature, in section 3 we describe the methodology and present the data sample, section 4 presents the empirical results, while section 5 is dedicated to analyzing and discussing the results, section 6 concludes the paper.

2 Theoretical Framework & Literature Review

In the following chapter, initially short-selling is introduced and the background of similar historical restrictions. Subsequently, the theoretical framework and a literature review of the role of short-sellers is presented followed by previous studies on the subject of short-selling restrictions. These studies vary in what type of crisis that is of interest and what markets that has been examined. Lastly, the chapter ends with the development of the hypothesis of this paper.

2.1 Short Selling

Short-selling a stock is a strategy used by an investor to profit or gain other advantages from a decline in the price of the stock, i.e., a short seller has a negative expectation of the stock or market. The strategy enables an investor to sell a stock by borrowing and therefore there is no need for the seller to actually own the stock. When an investor wishes to close the short position, the stock simply has to be bought back and the profit amounts to the difference between the selling and buying price. Further, there are different types of short-selling strategies and one that is frequently discussed is the so-called "Naked" short-selling. This type of short-selling occurs when an investor sells a stock they do not even possess at the time of the sale. (Siciliano & Ventoruzzo, 2020).

Something that has always been a controversy is the discussion whether or not short-selling is a desirable feature on the market. Some researchers deem that short-selling contributes to efficiency in markets in the way they eliminate price differences and arbitrage opportunities, but also as it increases market liquidity, and price discovery. Further, it also helps facilitate hedging strategies, mitigate bubbles and other activities involving risk management. (Arouri, Jawadi & Nguyen, 2012). Furthermore, as stated by Diether, Lee, and Werner (2009) short-sellers include a large majority of financial institutions and only a few individuals. Nonetheless, together they account for about 25% of daily trading in stocks subject to short sale price tests.

In contrast, others assess it to be contributing to undesirable increased volatility, especially during more extreme periods in the market. Further, investors not only use short-selling as a bet on falling stock prices but they could also use it in a way to influence and even determine the declining trend by selling large quantities of shares in that stock. Therefore, this strategy might force stock prices to fall even more than what is deemed reasonable by fundamentals and destroy the confidence of other investors in that specific stock. In other words, the company might have survived if it was not sold short in the first place. However, the fact that short-sellers might actually bring the prices back to their intrinsic value would make it a benefit to investors as they then are being protected from purchasing an overpriced stock. (Arouri, Jawadi & Nguyen, 2012).

Finally, as presented above short-selling as a market feature and strategy is extensively discussed and of great importance to be examined empirically (Bessler & Vendrasco, 2020; Siciliano & Ventoruzzo, 2020).

2.2 Historical Restrictions

The extensive debate on short-selling and whether it contributes or not to an efficient market has several times over the years led to interventions by market regulators (Jiang, Habib & Hasan, 2020). There are mainly three ways regulators can restrict or prohibit short-selling of securities according to the Financial Services Authority (2009). Firstly, restrict or prohibit short selling of all stocks. Secondly, restrict or prohibit so-called "Naked" short selling of financial stocks. Thirdly and finally, restrict or prohibit firms engaging in rights issues.

For instance, in 1931 the NYSE banned short-selling on downticks. Further, the Securities and Exchange Commission (SEC) in 1938 implemented an uptick rule[1] as a safety measure against so-called bear raids that was a frequently occurring phenomenon during the time. However, it was removed by the U.S. Securities and Exchange Commission (SEC) in 2007. In a so-called bear raid, short-sellers target a stock in which long investors have fully utilized their margin accounts. The stock price then declines as a result of aggressive short-selling of the stock and sometimes false rumors spread by the short-sellers. Hence, a margin call for long investors gets triggered by the decline and they also start selling which in turn make the stock decline even further. (Jiang, Habib & Hasan, 2020).

Other examples of regulatory interference as a reaction to steep declines in stock prices are the financial crisis 2008 and the aftermath of it, i.e., the Eurozone crisis. For instance, during the financial crisis the U.K Financial Services Authority and the SEC imposed short-selling restrictions, it was later followed by other countries such as Australia, France, Germany, Switzerland, Ireland, and Canada, among others. Furthermore, regulators in Europe imposed short-selling bans during the 2011-12 eurozone sovereign debt crisis. In both of these cases, in most countries, the short-selling restrictions mainly targeted financial institutions. More recently, during the Covid-19 pandemic crisis the decision was not uniform in Europe and only

[1] The uptick rule specifies that the short-selling transaction price of a stock has to be at least one tick higher than the price of the most recent trade with a different price (Jiang, Habib & Hasan, 2020).

a few European national market authorities decided to implement restrictions on short-selling. Namely, France, Spain, Italy, Austria, Greece, and Belgium. The restrictions referred to banning investors from engaging in short selling and other transactions that might constitute or increase net short positions in stocks. However, the European union regulation[2] that was used when opting to restrict investors' activities did not have a specific scenario for a pandemic. Although, it was argued to be considered a serious threat to market confidence and infrastructures and therefore be assessed to be included in the context of the regulatory framework. Furthermore, the EU regulator, European Securities and Markets Authority (ESMA) stated that price information sometimes may be misleading as a result of rumors or inexact information. Therefore, short-selling positions betting on negative news might destabilize the market even further and could lead to a self-reinforcing effect that causes an unjustified decline in stock prices. Consequently, restrictions regarding short-selling are deemed to be a tool to limit adverse consequences on volatility in stock markets and for the confidence of investors. (Beber et. al., 2020).

2.3 Theoretical Framework

Broadly speaking the theoretical literature on short-selling mainly goes back to Miller (1977) and Diamond and Verrecchia (1987). The argumentation made by Miller (1977) is that pessimistic traders are driven out of the market by short-selling constraints which in turn leads to prices only reflecting the valuations of the more optimistic traders, which may lead to overinvestment. Diamond and Verrecchia (1987) contrarily, focus rather on the speed of adjustment of security prices to private information. They argue that prohibiting traders from shorting reduces the adjustment speed of prices to private information, especially to bad news. Taken together, both of these studies argue that the presence of short sellers helps informational efficiency in markets by allowing prices to reflect the intrinsic value of securities and increasing the speed of adjustment for prices to new information. Restrictions on short-selling seem to reduce informational efficiency and therefore decrease the overall market quality.

In general, there seems to be a consensus in the literature that selling constraints bias security prices upward or downward (Miller, 1977; Jarrow, 1980; Figlewski, 1981). However, there are mixed financial theories on the actual role of short sellers, and they are either considered as informed traders that by actively trading move the mispriced securities closer to the

[2] Regulation (EU) No. 236/2012 and Article 24 of Regulation (EU) No. 918/2012 (Beber et. Al., 2020)

fundamental prices (Boehmer, Jones & Zhang, 2008; Diamond & Verrecchia, 1987). Else ways, they are seen as an actor in markets who make securities prices deviate from their fundamentals by predatory strategies and trade-based manipulation schemes (Allen & Gale, 1992; Brunnermeier & Pedersen, 2005; Goldstein & Guembel, 2008). Consequently, during so-called normal times on the market short sellers act as essential information intermediaries that strengthen the information environment (Jiang, Habib & Hasan, 2020). Although, during more turbulent times aggressive short-sellers might inflate the volatility and negative stock returns, this is especially true for smaller firms (Geraci, Garbaravicius & Veredas, 2018). The most critical risks are market manipulation and predatory investors leading to increased volatility and the mispricing of stocks (Allen & Gale, 1992; Brunnermeier & Oehmke, 2014). As a result, in times of turbulence on the markets, regulators might have to intervene in order to mitigate the risks so that the positive informational effects of short-selling can prevail (Bessler & Vendrasco, 2020). To sum up this discussion, according to Siciliano and Ventoruzzo (2020) most empirical papers has observed that in times of regular trading activity, short-selling has a positive effect on liquidity and price efficiency. Hence, supporting the statement that short selling is crucial to maintain a properly functioning market.

2.4 Literature Review

The academic literature studying the relationship between short-selling restrictions and its impact on market quality during times of crises appears to have established somewhat of a consensus. That there is a loss in market quality after a restriction has been imposed regardless of crisis. Numerous studies have examined the short-selling restrictions during the 2008 financial crisis and the aftermaths of it, the Eurozone crisis. The vast majority of these studies (e.g., Alves, Mendes & Silva, 2016; Beber et. al., 2020; Beber & Pagano, 2013; Boehmer, Jones & Zhang, 2013; Bohl, Reher & Wilfling, 2016; Helmes, Henker & Henker, 2017) conclude that restrictions negatively affect market quality, i.e., liquidity, volatility and the price discovery mechanisms. However, there are of course minor differences in the results from these studies as a result of different samples, time periods, methodology and what hypothesis that has been tested.

2.4.1 Financial Crisis

In a study of 727 financial stocks in the US, Boehmer, Jones and Zhang (2013) examine the impact of short-selling restrictions during the financial crisis on market quality, shorting activity, the aggressiveness of short sellers, and stock prices. They use a control group of 727 non-banned stocks. By doing so, they find that large-cap stocks suffer a severe degradation in terms of market quality measured by spreads, price impacts, and intraday volatility. However, small-cap stocks are unaffected to a large extent. Another interesting finding is that banned stocks jump in price, but this seems to be a result of bailout programs rather than the short-selling ban. Furthermore, they state that due to their findings it is clear that the regulators failed to achieve the goals of the implementation of the short-selling ban. However, they argue that there could still be legitimate reasons to impose them, for example manipulative shorting strategies could most likely have been a risk for financial stocks at this time. Finally, they conclude that it would still be a need for a large benefit in order to offset the large costs associated with large transaction costs and elevated volatility that was experienced by the market participants.

In a similar study, Beber and Pagano (2013) also study the financial crisis and the effects of the implementation of short-selling restrictions. However, the sample in this study is much larger as it consists of 16 491 stocks from 30 countries over the period January 2008 to June 2009. The implementation and lifting of the short-selling restrictions happened at different dates in different countries. Therefore, they use this variation to examine the effects of short-selling restrictions impact on liquidity, price discovery and stock prices. Their findings are in line with other studies of the financial crisis, and they suggest that the restrictions were detrimental to market liquidity, it slowed price discovery and therefore it was at best neutral in stock price stabilization. In a later paper by Beber et. al (2020) a similar approach is applied but unlike similar studies including only one of the crises, both the financial crisis and the eurozone crisis are included. Common to both crises are that regulators imposed short-selling restrictions in an attempt to stabilize the stock prices during such turbulent times. Therefore, their study differs from earlier studies with its wider coverage, based on data for two crises, including several countries and using various measures for stability. The final sample consists of 13 473 stocks for the first crisis and 16 424 stocks in the second including data from 25 countries of which 17 European countries and 8 non-European countries including for example the US, Australia, Canada and Japan. Hence, they cover all the main developed countries. The main purpose of the study is to investigate if the short-selling restrictions lead to a stabilization of vulnerable banks at times of market stress. In order to do so, they compare the change of solvency measures, volatility and stock returns. The findings indicate that short-selling restrictions, especially for banks, tend to be correlated with greater return volatility, a higher probability of default and steeper stock price declines. Lastly, they argue that one possible reason is that the silencing of the most critical investors weakens the discipline imposed by markets on bank managers' risk taking.

There are also examples of papers that focus solely on specific markets during the financial crisis, such as Bohl, Reher and Wilfling (2016) and Helmes, Henker and Henker (2017). The former investigates the German stock market by using stocks from the DAX-index both as test and control group and the latter compares Australian financial stocks with matched Canadian stocks. More specifically, Bohl, Reher and Wilfling (2016) investigated the volatility of stock returns before and during the implementation of short-selling restrictions in September 2008 until July 2010 on the German stock market. The sample group consists of 10 companies from the DAX-index and a control group of the remaining listed companies that was not affected by the short-selling restrictions. They construct an index by combining the companies and therefore avoid analyzing the volatility effects on a single stock. Earlier studies have focused more on the changes in volatility levels, but they instead focus on volatility persistence, defined as investors' limited ability to find the fundamental price during periods of short selling constraints. In order to analyze the effects, they applied two distinct versions of an asymmetric Markov-switching GARCH-model. They find an overall increase in the conditional variances for the German stock market after the collapse of Lehman Brothers. Although, they point out that they found an increase in volatility persistence and that the effect is especially pronounced for stocks affected by the short-selling restriction. Therefore, they argue that this can be seen as an evidence of a destabilizing impact of short selling constraints on the volatility of stock returns. Finally, they state an explicit recommendation to regulators not to impose short-selling restrictions in order to try and contribute to a stabilization to stock prices during a market downturn. This view is shared by Helmes, Henker and Henker (2017) that also conclude that the stated goal of calming the market was not achieved by implementing the short-selling ban for 45 Australian financial stocks. Canadian financial stocks are used as the control group as they are argued to have similar industry and regulatory characteristics as Australian financial stocks. In order to compare the effects of the ban before, during and after the ban with the Canadian financial stocks they apply an event study with the help of fixed-effect panel models. They employ a matching procedure along with a fixed-effect panel methodology. Firstly, firms were matched as closely as possible by the Global Industry Classification System (GICS) code. Secondly, pairs were formed by minimizing the difference in market capitalization between the two chosen firms based on a set tolerance level. Finally, two hypotheses were tested to examine the effects of the September 2008 shorting ban on volatility and market quality by comparing banned financial firms to non-banned financial firms. Their findings argue against the stated reasons for the implementation of the short-selling ban. They did not find any evidence for reduced volatility or stabilization of stock prices as a result of the short-selling ban. On the contrary, a severe degradation in market quality, i.e., an increase in intraday volatility, reduced trading activity and increased bid–ask spreads was observed.

2.4.2 Eurozone Crisis

In contrast, there are also papers investigating the effects of such a restriction during the Eurozone crisis. Alves, Mendes and Silva (2016) studied the impact of the temporarily short sale ban that was imposed by France, Belgium, Spain and Italy in August 2011. The aim of the ban was to reduce volatility and stop, or at least, mitigate the downward spiral in stock prices. The ban that at first was intended to last for only 15 days was kept in place until February 2012. In order to study whether the ban was effective in this context or not they investigate the effects on market quality, i.e., liquidity, volatility and price discovery mechanisms. Furthermore, the impact on the price dynamics of securities covered by the bans is evaluated. In order to do so they made a comparison of the period before and during the actual short-selling ban. The sample consisted of 170 financial stocks listed in Western Europe, of which 58 shares were subject to the actual short-selling ban and the remaining ones represented the control group. Instead of using the standard deviation as a measure for volatility they use a Garman-Klass volatility estimator which they argue contains more information and is thus a more robust indicator of volatility. The results presented are that firstly, financial stocks in countries that applied bans exhibited higher abnormal returns. Secondly, the bans had a negative effect on liquidity as the bid-ask spread and the Amihud illiquidity measure hiked after the implementation of the ban, and it was significantly higher for the stocks subject to the ban. Thirdly, they report an upsurge in volatility following the ban for all stocks, however the stocks that were subject to the ban experienced a bigger increase in volatility compared to the control group. The difference between the volatility of the groups was 3.2% points before and 7.9% points during the ban. They also conclude that the change in volatility after the ban was 10.3% points higher for the stocks that got banned. Finally, they also add that the percentage of financial stocks that experienced a volatility decline in two weeks following the ban is higher amongst the control group. Altogether, they argue that this implies that regulators appear to have failed to reduce volatility surges by implementing the restrictions.

2.4.3 Covid-19 Pandemic

In the most recent event of short-selling restrictions, six European countries implemented them during the Covid-19 pandemic in the beginning of 2020 and it has been studied to some extent. Both Bessler and Vendrasco (2020) and Siciliano and Ventoruzzo (2020) study the effects of the short-selling restrictions implemented by France, Italy, Spain, Belgium, Austria and Greece on market quality, i.e., abnormal returns, liquidity and volatility. However, they apply slightly different approaches in order to do so. Bessler and Vendrasco (2020) use spreads, turnover, price range and volatility to measure the impact on market quality. Further, they use the same number of European countries in the control group as in the treatment group and they split the time period into four different sub-periods, pre-crash (1/2 - 2/19), crash (2/20 - 3/17), ban (3/18 - 5/18) and post-ban (5/19 - 6/30). In order to construct a matched sample of stocks from ban and no-ban countries they use a propensity score matching without replacement. Using market capitalization and two digits SIC codes as the matching for the propensity score. A fixed-effects panel regression is performed. Furthermore, a distinction between smaller and larger stock markets is made when analyzing the results. The findings indicate that market quality is lower, i.e., liquidity and turnover decrease, and spreads, price range and volatility increase, during the ban period for the restricted stocks. Furthermore, banks are less affected, and the effect was relatively stronger in negative terms for smaller firms in smaller markets. Finally, it is stated that in hindsight the introduction of short-selling bans for market quality reasons are not justified in accordance with their findings. Contrarily, countries that did not impose bans although there was ample political pressure to do so seems to have made the right decision.

Similarly, Siciliano and Ventoruzzo (2020) examine the effects of the short-selling bans on market quality focusing mainly on two measures, abnormal return and liquidity. They also include a few more countries, as 14 European countries and the UK are examined. Data from 24th of January until 18th of May 2020 is used, the latter is when the bans were lifted for all countries. In contrast with the earlier mentioned study by Bessler and Vendrasco (2020) they also include the two one-day bans that were introduced in a few of the countries prior to the two-month long ban that both studies include. There are 1 356 stocks in the sample of which 242 were banned in at least one of the one-day bans and all of them in the two month long one. A difference-in-difference strategy is used for end-of-day data where the LHS-variables are abnormal returns and liquidity. The findings suggest that banned stocks had lower liquidity, higher information asymmetry and lower abnormal returns compared to non-banned stocks. These findings follow prior theoretical arguments and empirical evidence in other settings, i.e., that short-selling restrictions are not effective in stabilizing financial markets during periods of increased uncertainty. Similar to earlier studies and in particular Bessler and Vendrasco (2020) that also study the Covid-19 crisis they find that the restrictions appear to undermine the stated goals of market regulators. Further, they find that the effects are more pronounced for financial stocks, one reason for this is discussed in accordance with previous studies that the price discovery mechanism associated with short-selling is greater in the financial industry. Finally, the conclusions of the both above mentioned studies argue that financial regulators should be cautious in their decisions to introduce short-selling bans during market crises, given these bans' lack of effectiveness and negative consequences on market quality. However, both papers also discuss that there might be political reasons or political pressure for implementing such restrictions.

A brief summary of the previous above-mentioned studies can be found in Table 13 in the Appendix.

2.4.4 Hypothesis Development

The theoretical literature on short-selling and its predictions mainly goes back to Miller (1977) and Diamond and Verrecchia (1987). Both of these studies argue that the presence of short sellers helps informational efficiency in markets by allowing prices to reflect the intrinsic value of securities and increasing the speed of adjustment for prices to new information. Hence, short-selling restrictions seem to reduce informational efficiency and therefore decrease the overall market quality, i.e. increase volatility. Thus, following the predictions of previous theoretical papers we investigate the volatility before and during the actual restriction with the aim to answer the question whether restrictions were effective in reducing the volatility. Consequently, we test the following hypothesis:

The short-selling restrictions during the Covid-19 pandemic did not have an impact on the reduction of volatility

3 Methodology

In the following chapter the methodology of the study is presented. To begin with, the chosen model is introduced followed by extensions to it. Further, the underlying assumptions and the validation of the model is discussed. Moreover, the three different approaches used to analyze the research question is presented. Subsequently, the sample and its delimitations are discussed. Finally, the modeling of volatility, the Garman-Klass volatility estimator and the realized volatility is presented.

3.1 Difference in Difference Estimator

In order to analyze the effects that the short-selling restriction had on volatility in the treated countries, we apply a Difference-in-Difference method that is able to isolate the causal effect of the restriction, i.e., the treatment. Previous studies (e.g., Alves, Mendes & Silva, 2016; Beber & Pagano, 2013; Boehmer, Jones & Zhang, 2013; Siciliano & Ventoruzzo, 2020) have used a similar method in order to analyze the effect of the short-selling restriction during different crises. The reasoning behind choosing this method is that we have a before and an after period, and a treated and non-treated group. The Difference-in-Difference estimator combines two single difference estimators. The "cross-sectional comparison" (1) compares two different groups over the same time period and by doing this it avoids the problem of omitted trends (Roberts & Whited, 2013). The difference between the groups is captured by the parameter γ, since the dummy variable D_g takes the value of 1 if the group is affected by the restrictions.

$$y = \alpha + \gamma D_g + u \tag{1}$$

The time series comparison (2) examines a single group before and after the treatment and by doing so it captures the difference in treatment. The dummy variable D_t takes the value of 1 post treatment. Therefore, the parameter β captures the difference created by time.

$$y = \alpha + \beta D_t + u \tag{2}$$

The Difference-in-Difference estimator combines the cross-sectional comparison with the time series comparison and therefore avoids both the problem of omitted trends and unobserved differences between groups. (Roberts & Whited, 2013).

By combining (1) and (2) and adding an additional dummy that take the value of 1 for the treatment group in the treatment period we receive the following base model that we will proceed from:

$$y_{igt} = \alpha + \gamma D_g + \beta D_t + \delta D_{gt} + u_{igt} \tag{3}$$

D_g is a dummy variable that takes the value of 1 if the asset is part of the group that is affected by the short-selling restriction and 0 if it is not affected. The parameter γ will capture the group fixed effect of the companies that are affected by the restriction. D_t is a dummy variable that takes the value of 1 for all companies after the restriction on short-selling is introduced. The parameter β will capture the period fixed effect between prior and post restriction implementation. The final dummy variable D_{gt} is a product of the prior two dummy variables, it only takes the value of 1 if the asset is in the group that is affected by the restriction and after the implementation of the short-selling restriction. Therefore, the parameter δ will isolate the causal effect of the short-selling restriction (Roberts & Whited, 2013). Table 1 represents all the parameters to visually show the procedure and what parameters explain the different effects.

Table 1 – Parameter interpretations

	After	Before	Difference
Restricted	α + γ + β + δ	α + γ	β + δ
Non-restricted	α + β	α	β
Difference	γ + δ	γ	δ

3.1.1 Difference-in-Difference Extensions

By adding an extra term, $X\Gamma$ that represents additional exogenous variables into the base DD-regression (3), it is possible to check for efficiency and randomization. Roberts and Whited (2013) state that one of the underlying assumptions in a Difference-in-Difference estimation is that the assignment of treatment is in fact random, i.e., each security should have the same probability of receiving a short-selling restriction. If this assumption holds, adding extra exogenous variables should have a negligible effect on the treatment effect. If this assumption would not hold, then the average difference in volatility between the groups and time period can in fact be explained by other variables making the restriction less significant or even insignificant.

$$y_{igt} = \alpha + \gamma D_g + \beta D_t + \delta D_{gt} + X\Gamma + u_{igt} \tag{4}$$

3.1.1.1 Explanatory Variables

Zaremba, Kizys, Aharon and Demir (2020) state that stock market volatility is especially affected by government policies during the Covid-19 pandemic. In order to differentiate the effect from the short-sale restriction compared to other internal government interventions an inclusion of additional explanatory variables that explains a wider view of government actions is of great importance for the validity of the results. Siciliano and Ventoruzzo (2020), chose to include the natural logarithm of stringency as an independent variable. Which is an indicator that takes a value between zero and 100 depending on the average value of nine indications that represent the containment and closure policies during the Covid-19 pandemic. The stringency variable is provided by a collaboration between Blavatnik School of Government and the University of Oxford, who also provide three other Covid-19 related variables. The first one is an economic support index which measures income support and debt relief. The second one is a containment and health index that tracks lockdown restrictions, investments in healthcare and vaccine. The final index, the government response index is composed by all of the earlier mention indices. (Hale, Angrist, Goldszmidt, Kira, Patherick, Phillips, Webster, Cameron-Blake, Hallas, Majumdar & Tatlow, 2021). Based on the framework by Siciliano and Ventoruzzo (2020), we include the natural logarithm of the stringency index, but also the natural logarithm of the economic support index and the containment & health index. We exclude the government index since it is already indirectly included in the other indices.

3.1.2 Validation

3.1.2.1 Parallel Trends

Schwerdt and Woessmann (2020) argue that one of the most important assumptions of the Difference-in-Difference estimation is the identification assumption implying that the group-specific trends in the response variable would be identical in the absence of the treatment. In the context of this study, this means that in the absence of treatment the treated companies and the control groups volatility should be affected by Covid-19 and other external events in the same way. This assumption is often called the "parallel trends" assumption, since it requires the trends prior the treatment is equal between the groups. Roberts and Whited (2013) state that it is not possible to formally test the parallel trend assumption since it is an endogenous problem. However, they present two tests that are necessary and that can be comforting. Although, they are not sufficient to say that the endogeneity problem has been solved. The first is an ocular inspection of the cross-sectional data. The second one is a statistical test, more specifically a paired sample t-test. The test checks if the average growth rate in volatility between the groups is significantly different from zero, which represents the null hypothesis in the test. If the null hypothesis is rejected, the two groups have different trends prior to the restriction and a Difference-in-Difference estimation is therefore not applicable. The paired sample t-test is given by the following equation:

$$t = \frac{\overline{x}_{diff} - 0}{S_{\overline{x}}} \tag{5}$$

Where

$$S_{\overline{x}} = \frac{S_{diff}}{\sqrt{n}} \tag{6}$$

Where

$\overline{x}_{diff}$	is the sample mean of the differences
S_{diff}	is the sample standard deviation of the differences
$S_{\overline{x}}$	is the estimated standard error of the mean
n	is the sample size

3.1.2.2 Multicollinearity

Three explanatory variables are included into the analysis. Namely, stringency index, economic support index, and containment & health index. These variables mainly take values that are different from zero around the same time, mid-March 2020 and forward. Therefore, we check for multicollinearity in order to prevent individual coefficients to have high standard errors and low significance levels. As a result of multicollinearity, reliable inference is not possible and therefore, has to be accounted for (Daoud, 2017). We apply the variance inflation ratio (VIF) that tests the severity of multicollinearity by measuring how much the variance is inflated in the coefficients from the difference-in-difference regression. The VIF equation is as follows:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{7}$$

Where

R_i^2 is the R-squared value that is estimated by running an OLS-regression, where one explanatory variable is the function of the remaining explanatory variables.

3.1.3 Synthetic Control Group

The parallel trend is considered the most fundamental and important assumption to be satisfied to get reliable results from the application of the Difference-in-Difference estimator. Robert and Whited (2013) state that the consequence of this assumption being a necessity is that as earlier stated, there is no formal way of testing this assumption that guarantees that it is satisfied (Robert & Whited, 2013). However, by following the framework presented by Hollingsworth and Wing (2020) that builds on the original methodology created by Abadie, Diamond and Hainmueller (2010). It is possible to create a synthetic control group by implementing an ordinary least squares regression on the pre-restriction data, i.e., the data before the 18th of March, 2020. Where the volatility for the restricted countries is the dependent variable, while the volatility for the control countries is the explanatory variables, the coefficient outputs is therefore the weights for the synthetic control group and they are chosen by minimizing the sum of squared difference between the true pre-restriction data and the estimated synthetic control group. The summation of the estimated weights is set to be equal to 1, and each weight separately is set to be equal to, or larger than 0, which in our paper gives the same intuition that we cannot go short in an index, or leverage a specific index. The following equation shows the estimated weights that are obtained by the OLS application:

$$\widehat{\omega}_{OLS} = \arg min_{\omega} \left(\sum_{t=1}^{T_0} (y_{0t} - x_t \omega)^2 \right) \tag{8}$$

Where

$\widehat{\omega}_{OLS}$ is the coefficient outputs from the OLS regression

T_0 is the latest observation prior to the restriction

y_{0t} is the volatility for the restricted group at time t

x_t is the volatility for the non-restricted group at time t

ω is the corresponding weight to each explanatory variable

Hollingsworth and Wing (2020) state that the disadvantage with the OLS methodology is that it creates parameters that will cause overfitting in the pre-restriction data and therefore low out of sample prediction. This translates to that the pre-period weights for the different countries are not necessarily good in the post-period. However, the purpose of the creation of a synthetic control group, is that it will force the Difference-in-Difference estimation to satisfy the assumption of parallel trends, since it is made with the objective to minimize the pre-restriction difference between the control- and treatment group.

3.2 Research Design

In order to analyze the effect of the short-selling restriction we design three different approaches. In the first one, the index approach, we analyze the volatility change on an index level. Bohl, Reher and Wilfling (2016) also apply such an approach in order to avoid analyzing the volatility effects on a single stock. However, they construct the index themselves since only selected financial stocks were subject to the restriction during the financial crisis. While in the second one, the decomposed approach, we follow the majority of previous studies (e.g., Alves, Mendes & Silva, 2016; Beber et. al., 2020; Beber & Pagano, 2013; Bessler & Vendrasco, 2020; Boehmer, Jones & Zhang, 2013; Helmes, Henker & Henker, 2017) by narrowing the view and analyze the individual stocks in the respective indices. In the third and final approach, we only analyze stocks that are included in the financial sector based on the global industry classification standard (GICS). The reason for this is that previous literature mainly focuses on this specific sector. In all three approaches we analyze the difference in volatility between the control group and the treatment group. Therefore, volatility will be the dependent variable in the Difference-in-Difference regressions.

3.2.1 Index Approach

In the first approach the treatment group consists of the three main indices in the following countries, Austria, Belgium and France and the control group are based on the three main indices in Germany, the Netherlands and Sweden. One downside with this approach is that there are a few stocks that are cross listed, i.e., the treatment indices include a few stocks that are not actually affected by the restrictions since their main listing is in another country that does not introduce any short-selling restrictions. The six indices, ATX, BEL20, CAC40, DAX, AEX and OMXS30 that are included into the analysis are all market-cap weighted, i.e., each stock is connected to a corresponding weight. A possible drawback with this is that one stock may have a big impact on the results. In other words, the results that are obtained may be highly driven by a few companies. However, we still proceed with this approach since its still economically true that few companies have a bigger effect on certain parameters, one of them being market volatility. We will use the synthetic control group for this specific approach, by analyzing these results in combination with the outputs obtained from the standard control group, it is possible to check for coherency between the two different control groups, and therefore robustness and validation of the overall result.

3.2.2 Decomposed Approach

In order to solve the potential disadvantages with the index approach, we decide to include a second procedure, where we decompose the indices which makes it more flexible when it comes to what securities are included in the control group and treatment group. All securities from each index are included, which is similar to the first approach, however, we now exclude cross-listed stocks, and they are all equally weighted. By creating an equally weighted portfolio, each security will have the same effect on the results (Cooperate finance institute, n.d.).

3.2.3 Financial Sector Approach

As a third approach we analyze a sub-group of financial securities. The sub-group includes all the financial securities from the main indices in the six different countries. By doing this, we can test for differences in the financial sector. This is of specific interest since the majority of previous literature mainly focuses on financial securities, due to the fact that earlier short-selling restrictions mainly was implemented on financial stocks.

3.3 Sample

3.3.1 Delimitations

Due to a limited time horizon and the scope of this study some delimitations are necessary. To start with, six countries introduced a short-selling restriction on the 18th of March 2020. We use a treatment group of three countries and these are matched with three other countries constituting a static control group, i.e., the countries in the control group stays the same. Hence, in order to get reliable results, the treatment- and control group should be similar and therefore the countries constituting each group indirectly also have to be similar. As a result, to be included in the sample they had to satisfy three specific parameters. Firstly, they have a credit score equal to or higher than A from all of the three main agencies[3]. In order to make the

[3] The three main agencies are Moody's, S&P Global Ratings & Fitch Ratings

treatment and control group comparable with respect to financial characteristics. Secondly, in accordance with previous studies (e.g., Helmes, Henker & Henker, 2017; Alves, Mendes & Silva, 2016) they share the same regulatory characteristics and contain similar industry distributions. In effect, both groups react to the same supply and demand shocks, share the same regulatory environment, competing in the same banking industry, and also a portion of their earnings is expected to co-move over time (Alves, Mendes & Silva, 2016). Resulting in that out of the six countries that introduced a restriction, Austria, Belgium and France are included in the study and Greece, Italy and Spain are excluded. They are excluded due to not fulfilling the first assumption of credit score (Fitch Ratings, n.d.; Moody's, n.d.; S&P Global Ratings, n.d.). Choosing the control group is of great importance since both the treatment and control group should be directly comparable (Alves, Mendes & Silva, 2016). The reason for that the control and treatment group should contain the same industries is that we assume that Covid-19 hits industries heterogeneously. Thus, in the absence of the short-selling restriction the two different groups would be equally affected. Therefore, we decided to limit the control group to European countries since they share a lot of the same regulations. To further restrict the choice of countries we analyzed what sectors were dominating in the treatment group, based on the GICS. The majority of the companies in Austria, Belgium and France operate within the financial- and the industrial sector. Hence, we chose Germany, the Netherlands and Sweden as a control group based on the parameters that they have similar credit ratings, regulations and that their proportions within the same sectors are similar. The distribution of sectors for both the treatment and control group can be seen in Table 14 in the appendix.

Another delimitation is the selected sample period for this study. We limited the time period prior to the implementation of the restriction to six months, i.e., the time period analyzed in this study is the 18th of September 2019 to the 18th of May 2020 and including the restriction this amounts to eight months in total.

Lastly, France introduced a one-day ban on the 17th of March 2020. However, we did not include this ban in the treatment group based on the argumentation by Siciliano and Ventoruzzo (2020) and the non-inclusion of them in Bessler and Vendrasco (2020). Both of these papers study the Covid-19 pandemic crisis. Siciliano and Ventoruzzo (2020) state that the reason for removing them was the high likelihood of omitted variables driving the results. The basis of this argument derives from the fact that this one-day ban is a result of an endogenous decision by the market regulators to protect the most hard-hit stocks. They do this since it is not possible to rule out that the implementation of the short-selling bans was random. Furthermore, Bessler and Vendrasco (2020) do not include the one-day bans into their sample at all.

3.3.2 Data

For the purpose of this paper, we extracted data from DataStream for our sample that includes stock and index data from six European countries. Initially, there were 165 individual stocks included in the sample. Although some stocks were cross-listed, and others were replaced from the indices during the sample period. Thus, after these were excluded, the final sample consisted of 153 individual stocks. We collected daily data between the 30th of August 2019 and the 18th of May 2020, for both the indices and securities. For the index approach we collected daily high-, low-, close- and open prices for ATX, BEL20, CAC40, DAX, AEX and OMXS30 to be able to calculate the daily volatility with the Garman-Klass estimator. For the decomposed- and financial approach we used daily data to calculate monthly volatility. The period of the restrictions stretched from the 18th of March 2020 until the 18th of May 2020, after cleaning the data from missing observations there were 40 daily observations for each stock left in the treatment period. For the non-treatment period we used a time period of six months. In order to calculate the monthly realized volatility, we used a moving window with the size of 20 observations, i.e., each daily observation contains the past 20 days realized volatility. The number of observations in the different groups for the three separate approaches are given in the following table.

Table 2 - Sample distribution by group and country

Index Approach - Daily

Treatment Group		Control Group	
Country	No. Obs.	Country	No. Obs.
Austria	164	Germany	164
France	164	Netherlands	164
Belgium	164	Sweden	164
Total number of observations – 984			

Decomposed index Approach – Monthly

Treatment Group		Control Group	
Country	No. Obs.	Country	No. Obs.
Austria	3160	Germany	4 424
France	5 846	Netherlands	3 634
Belgium	2 528	Sweden	4 582
Total number of observations – 24 174			

Decomposed Financial Sector Approach - Monthly

Treatment Group		Control Group	
Country	No. Obs.	Country	No. Obs.
Austria	790	Germany	632
France	632	Netherlands	948
Belgium	790	Sweden	948
Total number of observations – 4 740			

3.4 Modeling Volatility

Volatility is included as the dependent variable in the Difference-in-Difference estimator in order to study the effect that short-selling restrictions have on volatility. Since, volatility is a latent variable and not directly observable, it needs to be estimated with a model using historical data (Tsay, 2010). Preferably one should use high frequency intraday data, such as 5-minute intervals to calculate daily realized volatility. However, due to data limitations we use the Garman-Klass estimator to calculate the daily volatility for each index, which represents the first approach, for the decomposed index and financial sector approach we instead use daily return data to calculate monthly volatility.

3.4.1 Garman-Klass Volatility Estimator

In the first approach, we follow Alves, Mendes and Silva (2016) and calculate the daily volatility for the six different indices utilizing the Garman-Klass volatility estimator. They argue that this estimator includes more information about the intraday movements of an asset and is thus a more robust indicator of volatility. The model contains information about intraday highs, lows, closing price and opening price of a security. These four parameters therefore act as proxies for intraday volatility and intraday spikes. N represents the size of the sub-sample, i.e., how large the moving window containing the four parameters will be, we set the sub-sample size, N equal to 20. Therefore, each volatility will be based on 20 historical data points. Fiszeder (2013) argue that a downside when modeling volatility with this estimator is that it does not consider the opening jump in index prices. The overnight jumps introduce a bias in the modeling of volatility. The Garman-Klass volatility is estimated with the following equation:

$$\sigma_t = \sqrt{\frac{1}{N} * \sum_{i=1}^{N} \left(\frac{1}{2} * \ln\left(\frac{H_i}{L_i}\right)\right)^2 - \frac{1}{N} * \sum_{i=1}^{N} (2 * \ln(2) - 1) * \ln\left(\frac{C_i}{O_i}\right)^2} \quad (9)$$

Where

H_i	is the highest intraday price of an asset
L_i	is the lowest intraday price of an asset
C_i	is the closing price of an asset
O_i	is the opening price of an asset

3.4.2 Realized Volatility

For the decomposed- and financial sector approach we instead use realized volatility and the reasoning behind this is based on the discussion in Andersen and Bollerslev (1998). This led us to the decision not to use a GARCH-model in order to estimate volatility. Because, we analyze a period that has already occurred, we have no use in forecasting volatility. Instead, we estimate the volatility that has already happened, i.e., the realized volatility. Further, the realized variance is calculated by taking the summation of the returns squared during any period and the realized volatility is given by equation (11) and is the square root of the realized variance. Since we calculate monthly volatility for the two different approaches, N will be equal to the amount of trading days in a month, hence N is set to 20. For example, the monthly volatility observation calculated on the 18th of May 2020 is based on the subsequent 20 trading days prior to this date.

$$Realized\ Variance = \sum_{i=1}^{N} r_t^2 \tag{10}$$

$$Realized\ Volatility\ = \sqrt{Realized\ Variance} \tag{11}$$

Where

r_t	is the daily return calculated with $Ln(S_t) - Ln(S_{t-1})$
S_t	is the stock price at time t

4 Empirical Results

The following chapter present the results of the study based on the data collected and based on the tests performed to answer the study's research question. Initially, descriptive statistics are presented, then the regression result for each approach is presented and this constitutes the basis for answering the research question. Finally, the validation of the results with regard to both a visual inspection and a formal statistical test is performed.

4.1 Multicollinearity & Modified Difference-In-Difference Estimator

Table 3 - Correlation Matrix

	RV	β	γ	δ	*E I*	*H&C I*	*S I*
RV	1						
β	0.73	1					
γ	0.02	0	1				
δ	0.52	0.64	0.39	1			
E I	0.73	1	0.04	0.69	1		
H&C I	0.73	0.99	0.01	0.65	0.99	1	
S I	0.73	0.99	0.012	0.65	0.99	0.99	1

Note: Table 3 displays the results of the correlation matrix. The threshold for severe multicollinearity is > 0.8. Variables in matrix are (1) RV - Realized Volatility, (2) β - Time Fixed Effect, (3) γ - Group Fixed Effect, (4) δ - Treatment Effect, (5) E I - Economic support Index, (6) H&C I - Healthcare & Containment Index and (7) S I – Stringency Index.

The consequence of the similarities between the Stringency-, Economic- and Health & Containment Index is that they suffer from very high correlation between each other. This in turn, leads to that they cannot be included in the same model, since it will cause multicollinearity, and therefore make the results unreliable. The VIF values are displayed in Table 15 in the Appendix, and corresponds with the results from the correlation matrix, that the β-parameter, and the Covid-19 trackers are strongly correlated. Since the three Covid-19 indices all start to take values mid-March 2020 and forward, they also have a high correlation factor to the β-parameter, i.e., the Time Fixed dummy. Since, this dummy variable takes the value of 1, for the 18th of March 2020 and post this date. However, since the β-parameter and each respective index have such a high correlation, it is possible to use each index separate as a proxy for the time fixed effect. Which leads to the modified Difference-in-Difference estimator, that is inspired by the equation provided by Roberts and Whited (2013) and the methodology that was presented by Siciliano and Venturozzo (2020):

$$y_{igt} = \alpha + \gamma D_g + \delta D_{gt} + X\Gamma + u_{igt} \quad (12)$$

Where

D_g	is a dummy variable that takes the value of 1 for the treated group
D_{gt}	is a dummy variable that takes the value of 1, for the treated group in the restricted period
$X\Gamma$	is a representation of the three Covid-19 indices

The γ parameter will capture the difference between the treated and non-treated group, δ is still the treatment effect, and X will capture both the time difference, but also the impact of the different Covid-19 indices. The reasoning behind the inclusion of these variables, is that they give more information than a dummy variable, that only takes the value of 0 or 1.

4.2 Base Difference-in-Difference Results

4.2.1 Index Approach

Table 4 - Regression Results (Index)

Dependent variable: Volatility (Daily)		
No. Observations: 984	Adjusted R-Square: 0.36	Significance-F: 0 ***
Parameter	Coefficient	P-Value
α (Intercept)	0.0080	0 ***
	(0.0004)	
β (Time Fixed Effect)	0.0123	0 ***
	(0.0008)	
γ (Group Fixed Effect)	0.0005	0.42
	(0.0006)	
δ (Restriction Effect)	0.0035	0.0041 ***
	(0.0012)	

Note: Table 4 displays the results of the difference-in-difference regression where daily index volatility is a function of an intercept, time fixed effect, group fixed effect and the treatment effect which represents the restriction effect. The coefficients are in daily values, i.e., daily volatility. Details about what combination of parameters represents what are presented in Table 1. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to a P-Value that is assigned either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05) it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed. The variables that are included in Table 4 are (1) Time Fixed Effect, that is a dummy variable that takes the value equal to 1 post implementation of restriction, (2) Group Fixed Effect, is a dummy variable that takes the value of 1 if the observation is included in the treatment group and 0 if it is in the control group, (3) Restriction Effect or Treatment Effect is a dummy variable that takes the value of 1 for observations that are in the Treatment group, post the restriction implementation.

The results that are obtained from the Difference-in-Difference estimator when applying it to the index data is presented in Table 4. The total number of observations is 984 in the model and an adjusted R-square of 0.36 is received. The model shows statistically significant results for the Intercept, Time Fixed Effect and Treatment Effect (Restriction). All three parameters are significant on a 1%-level (P-value < 0.01). The three respective parameters also have positive coefficients. The Group Fixed effect has a coefficient close to 0 and is not significant on a 10%-level (P-value > 0.1), which indicates that there is no statistically significant difference between the treated group and the control group in the pre-restriction period. The estimated volatility in the pre-restriction period for the treated group is given by $\alpha + \gamma$, which results in a daily volatility of 0.85%. Contrarily, for the non-treated group in the same period, daily volatility is given by α, and therefore it had a daily volatility of 0.8%. The volatility for the treated group in the pre-restriction period is thus, 6.25% higher compared to the non-treated group. The volatility for the post-restriction period for the treated group is given by $\alpha + \gamma + \beta + \delta$, which leads to a daily volatility of 2.43%. Whereas, for the non-treated group, the volatility is given by $\alpha + \beta$, and it had a daily volatility of 2.03%. During the post-restriction period, the daily volatility for the treated group is 19.7% higher than for the non-treated group. The variable that we are analyzing specifically in this paper is the δ, since it isolates the casual restriction effect. As it is significant on a 1%-level and has a positive value of 0.35%, it gives the indication that the implementation of a short-selling restriction, in fact increased volatility instead of decreasing it.

4.2.2 Decomposed Index Approach

Table 5 - Regression Results (Decomposed Index)

Dependent variable: Volatility (Monthly)		
No. Observations: 24 174	Adjusted R-Square: 0.54	Significance-F: 0 ***
Parameter	Coefficient	P-Value
α (Intercept)	0.071	0 ***
	(0.0006)	
β (Time Fixed Effect)	0.1206	0 ***
	(0.0011)	
γ (Group Fixed Effect)	-0.0038	0 ***
	(0.0007)	
δ (Restriction Effect)	0.0279	0 ***
	(0.0016)	

Note: Table 5 displays the results of the difference-in-difference regression where monthly stock volatility is a function of an intercept, time fixed effect, group fixed effect and the treatment effect which represents the restriction effect. The coefficients are in monthly values, i.e., monthly volatility. Details about what combination of parameters represents what are presented in Table 1. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to a P-Value that is given either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed. The variables that are included in Table 5 are (1) Time Fixed Effect, that is a dummy variable that takes the value equal to 1 post implementation of restriction, (2) Group Fixed Effect, is a dummy variable that takes the value of 1 if the observation is included in the treatment group and 0 if it is in the control group, (3) Restriction Effect or Treatment Effect is a dummy variable that takes the value of 1 for observations that are in the Treatment group, post the restriction implementation.

In Table 5, the Difference-in-Difference estimation for the Decomposed Index Approach is displayed. The total number of observations is 24 174 and the model has an adjusted R-square of 0.54. All four parameters, Intercept, Time Fixed Effect, Group Fixed Effect and Restriction Effect are significant on a 1%-level (P-value < 0.01). The respective parameters, except the Group Fixed Effect have a positive coefficient. The estimated volatility in the pre-restriction period for the treated group is given by $\alpha + \gamma$, which results in a monthly volatility of 6.72%. Although, for the non-treated group in the same period, daily volatility is given by α, amounting to a daily volatility of 7.1%. Hence, the volatility for the treated group in the pre-restriction period is 5.4% lower compared to the non-treated group. The volatility for the post-restriction period for the treated group is given by $\alpha + \gamma + \beta + \delta$, which leads to a monthly volatility of 21.57%. Contrarily, for the non-treated group, the volatility is given by $\alpha + \beta$, and a monthly volatility of 19.16%. Further, for the post-restriction period the daily volatility for the treated group is 12.58% higher than for the non-treated group. The δ variable is significant on a 1%-level and has a positive value of 2.79%. Indicating that the implementation of a short-selling restriction, in fact increased volatility, instead of decreasing it. This result is similar to the abovementioned Index Approach.

4.2.3 Financial Sector Approach

Table 6 - Regression Results (Financial Sector)

Dependent variable: Volatility (Monthly)		
No. Observations: 4 740	Adjusted R-Square: 0.60	Significance-F: 0 ***
Parameter	Coefficient	P-Value
α (Intercept)	0.0708	0 ***
	(0.0012)	
β (Time Fixed Effect)	0.1415	0 ***
	(0.0024)	
γ (Group Fixed Effect)	-0.0088	0 ***
	(0.0018)	
δ (Restriction Effect)	0.0239	0 ***
	(0.0036)	

Note: Table 6 displays the results of the difference-in-difference regression where monthly financial stock volatility is a function of an intercept, time fixed effect, group fixed effect and the treatment effect which represents the restriction effect. The coefficients are in monthly values, i.e., monthly volatility. Details about what combination of parameters represents what are presented in Table 1. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to a P-Value that is given either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed. The variables that are included in Table 6 are (1) Time Fixed Effect, that is a dummy variable that takes the value equal to 1 post implementation of restriction, (2) Group Fixed Effect, is a dummy variable that takes the value of 1 if the observation is included in the treatment group and 0 if it is in the control group, (3) Restriction Effect or Treatment Effect is a dummy variable that takes the value of 1 for observations that are in the Treatment group, post the restriction implementation.

In Table 6, the Difference-in-Difference estimation for the final approach, when we analyze solely the financial sector is displayed. The total number of observations is 4 740 and the model has an adjusted R-square of 0.60. All four parameters, Intercept, Time Fixed Effect, Group Fixed Effect and Restriction Effect are significant on a 1%-level (P-value < 0.01), similar to the previous model. The respective parameters, except the Group Fixed Effect have a positive coefficient. The estimated volatility in the pre-restriction period for the treated group is given by $\alpha + \gamma$, which results in a monthly volatility of 6.2%. Further, for the non-treated group in the same period, daily volatility is given by α, and therefore the daily volatility amounts to

7.08%. Therefore, the volatility for the treated group in the pre-restriction period is 12.42% lower compared to the non-treated group. The volatility for the post-restriction period for the treated group is given by $\alpha + \gamma + \beta + \delta$, which leads to a monthly volatility of 22.74%. Contrarily, for the non-treated group the volatility is given by $\alpha + \beta$. Hence, the monthly volatility amounts to 21.23%. For the post-restriction period, the daily volatility for the treated group is 7.11% higher than the non-treated group. The δ variable is significant on a 1%-level and has a positive value of 2.39%. As for the previous two models, it gives the indication that the implementation of a short-selling restriction, in fact increased monthly volatility in the financial sector, instead of decreasing it.

4.3 Modified Difference-In-Difference Estimator

4.3.1 Index Approach

Table 7 - Modified Regression Results (Index)

Dependent Variable: Volatility (Daily)			
Parameter	Model 1	Model 2	Model 3
α (Intercept)	0.0062***	0.0075***	0.0053***
	(0.0004)	*(0.0004)*	*(0.0004)*
γ (Group Fixed Effect)	0.0009*	0.0007	0.0017***
	(0.0005)	*(0.0006)*	*(0.0009)*
δ (Restriction Effect)	0.0013	0.0006	0.0014
	(0.0009)	*(0.0012)*	*(0.0009)*
Stringency	0.0036***	-	-
	(0.0002)		
Economic Support	-	0.0035***	-
		(0.0002)	
Health & Containment	-	-	0.0038***
			(0.0002)
Adj. R-Square	0.4888	0.4239	0.4921
No. Observations	984	984	984

Note: Table 7 displays the results of the modified difference-in-difference regression where daily index volatility is a function of three different models. All three models include, an intercept (α), Group Fixed Effect (γ), Restriction effect (δ), while model one includes the Stringency index, model two, the Economical index and model three adds the Health & Containment index. Details about what combination of parameters represents what are presented in Table 1, with the exception of the index parameter. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed.

In Table 7, the modified Difference-in-Difference estimation for the index approach is displayed, where daily volatility is a function of three different models. The total number of observations for each model is 984. For model 1, where the Stringency index is added as an additional explanatory variable, the adjusted R-square value is 0.49. The model has two independent variables that are significant on a 1%-level (P-value < 0.01), the intercept and the Stringency index, both having a positive coefficient of 0.0062 and 0.0036, respectively. The Group Fixed Effect is significant on a 10%-level (P-value < 0.1) and has a positive coefficient with a value of 0.0009. The δ-variable that represents the treatment effect, or in other words what effect the short-selling restriction has on volatility is not significant on a 10%-level (P-value > 0.1). However, the coefficient is still positive, with a value of 0.0013. The estimated volatility for the pre-restriction period for model 1 for the non-treated group is given by α, which adds up to a daily volatility of 0.62%. For the same period, but for the treated group, the volatility is given by α + γ and results in a daily volatility of 0.629%. Hence, the treated group has a daily volatility that is 1.45% higher compared to the non-treated group for the period before the implementation of short-selling restrictions. For the restricted period, the daily volatility for the treated group is given by $\alpha + \gamma + \overline{X}\Gamma_{Stringency} + \delta$, which results in a daily volatility of 2.82%. For the non-treated group, the volatility is given by $\alpha + \overline{X}\Gamma_{Stringency}$, which leads to a daily volatility of 2.59%. The treated group therefore has a volatility that is 8.5% higher compared to that of the estimated volatility for the non-treated group, during the restricted period.

The second model has a R-square value of 0.4239 and only two significant parameters, the intercept and the Economic Support Index, both on a 1%-level (P-value < 0.01), both have a positive coefficient. Neither the γ- nor the δ-parameter are significant on a 10%-level. The estimated daily volatility for the pre-restriction period is 0.75% for the non-treated group and 0.82% for the treated group, implying that the treated group have a volatility that is 9.3% higher for this period compared to its control group. For the restricted period, the volatility for the treated group is 2.44% and for the non-treated group it is 2.31%, which results in a difference of 5.6% between the groups.

The third and final model has a R-square value of 0.4921, and three variables that are significant on a 1%-level, the intercept, the Group Fixed Effect, and the Health & Containment index, each with a positive coefficient. The estimated daily volatility for the pre-restriction period is for the non-treated group 0.53%, and for the treated group, 0.7%, mounting to a 34% difference in volatility between the groups for the given period. For the restricted period, the non-treated group have a daily volatility of 2.727%, on the other side, the treated group have a daily volatility 3.037%, which is 11.36% higher compared to the non-treated group for the same time period. For all three models the δ-variable have a positive coefficient which implies that the implementation of the short-selling restriction, increases volatility. However, none of the models display a significant δ-coefficient.

4.3.2 Decomposed Index Approach

Table 8 - Modified Regression Results (Decomposed Index)

Dependent Variable: Volatility (Monthly)			
Parameter	Model 1	Model 2	Model 3
α (Intercept)	0.0709***	0.0712***	0.0711***
	(0.0005)	*(0.0006)*	*(0.0006)*
γ (Group Fixed Effect)	-0.0035***	-0.0042***	-0.0038***
	(0.0007)	*(0.0008)*	*(0.0008)*
δ (Restriction Effect)	0.0226***	0.0134***	0.0236***
	(0.0016)	*(0.0017)*	*(0.0016)*
Stringency	0.0288***	-	-
	(0.0002)		
Economic Support	-	0.0299***	-
		(0.0002)	
Health & Containment	-	-	0.0298***
			(0.0002)
Adj. R-Square	0.5475	0.5392	0.5445
No. Observations	24 174	24 174	24 174

Note: Table 8 displays the results of the modified difference-in-difference regression where monthly decomposed index volatility is a function of three different models. All three models include, an intercept (α), Group Fixed Effect (γ), Restriction effect (δ), while model one includes the Stringency index, model two, the Economical index and model three adds the Health & Containment index. Details about what combination of parameters represents what are presented in Table 1, with the exception of the index parameter. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed.

In Table 8, results from the modified Difference-in-Difference estimation for the decomposed index is displayed, where monthly volatility is a function of three different models. The total number of observations for each model is 24 174. The first model that includes the Stringency index have an adjusted R-square value of 0.5475, which is the highest out of the three models. All four variables that are in the model, namely, intercept, Group Fixed Effect, Treatment Effect and the Stringency variable are all significant on a 1%-level (P-value < 0.01). Each variable has a positive coefficient except the Group Fixed Effect, that is slightly negative. The estimated volatility for non-treated group in the pre-restriction period is 7.09%, and in the same period the treated group have an estimated monthly volatility of 6.74%, which implies that the treated group have 4.94% lower volatility in the pre-restriction period, compared to the non-treated group. For the restriction period, the non-treated group has a monthly estimated volatility of 19.41%, while the treated group have a volatility of 21.32%, that is 9.8% higher than the non-treated group.

The second model has an adjusted R-square value of 0.5392. Each variable that is included in the model is significant on a 1%-level (P-value < 0.01), and similar to the first model, all coefficients are positive except the Group Fixed Effect. The estimated volatility for the non-treated group for the period before the short-selling restriction is 7.12%, and for the treated group it is 6.7%, which is 5.9% lower than the non-treated group. For the treated period, the non-treated group has a volatility of 19.81% while the treated group has a monthly estimated volatility of 20.73%, which is 4.6% higher compared to the non-treated group for the same time period.

The last and final model for the decomposed index, includes the Health & Containment index and have a R-square value of 0.5445. As in the two earlier models, all four variables are significant on a 1%-level (P-value < 0.01), and all are positive except the Group Fixed Effect. The model implies that the pre-restriction monthly volatility for the non-treated group is 7.11%, and for the treated group, it is 6.73%, i.e., 5.34% lower than the non-treated group for this specific period. For the restricted time period, the non-treated group has a monthly estimated volatility of 19.38%, while the monthly volatility for the treated group was 21.36%, which is 10.21% higher than the non-treated group.

The δ-parameter is positive and significant for all three models, which indicates that the restriction seems to lead to a volatility increase, rather than a decrease which was the stated purpose of the implementation of the restriction by regulators.

4.3.3 Financial Sector Approach

Table 9 - Modified Regression Results (Financial Sector)

Dependent Variable: Volatility (Monthly)			
Parameter	Model 1	Model 2	Model 3
α (Intercept)	0.0705***	0.0701***	0.0707***
	(0.0012)	*(0.0012)*	*(0.0012)*
γ (Group Fixed Effect)	-0.0085***	-0.009***	-0.0087***
	(0.0018)	*(0.0018)*	*(0.0018)*
δ (Restriction Effect)	0.0175***	0.0074**	0.0189***
	(0.0036)	*(0.0038)*	*(0.0036)*
Stringency	0.0338***	-	-
	(0.0005)		
Economic Support	-	0.0353***	-
		(0.0006)	
Health & Containment	-	-	0.0351***
			(0.0006)
Adj. R-Square	0.6115	0.6061	0.6081
No. Observations	4 740	4 740	4 740

Note: Table 9 displays the results of the modified difference-in-difference regression where monthly financial stock volatility is a function of three different models. All three models include, an intercept (α), Group Fixed Effect (γ), Restriction effect (δ), while model one includes the Stringency index, model two, the Economical index and model three adds the Health & Containment index. Details about what combination of parameters represents what are presented in Table 1, with the exception of the index parameter. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed.

In Table 9, results from the modified Difference-in-Difference estimation for the decomposed index approach solely examining stocks in the financial sector is presented. All three models are a function of monthly volatility. The total number of observations for each model is 4 740. The first model that includes the Stringency index has an adjusted R-square value of 0.6115, which is the highest out of the three models. All four variables that are in the model are significant on a 1%-level (P-value < 0.01). Each variable has a positive coefficient except the Group Fixed Effect, that is slightly negative. The estimated volatility for the non-treated group in the pre-restriction period is 7.05% and during the same period the treated group had an estimated monthly volatility of 6.2%. This implies that the treated group has a 12.1% lower volatility compared to the non-treated group in the pre-restriction period. Contrarily, for the restriction period, the non-treated group has a monthly estimated volatility of 21.57%, while the treated group have a volatility of 22.47%. Implying, that the volatility is 4.17% higher than for the non-treated group.

For the second model, the adjusted R-square value is 0.6061 and out of the four included variables all except the Restriction Effect, which is significant on a 5%-level (P-value < 0.05), is significant on a on a 1%-level (P-value < 0.01). Further, in similarity to the first model all coefficients are positive beside the Group Fixed Effect. The estimated volatility for the non-treated group for the period before the short-selling restriction is 7.01% and for the treated group 6.11%, which is 12.84% lower than for the non-treated group. Furthermore, for the treated period the non-treated group has a volatility of 21.99% while the treated group has a monthly estimated volatility of 21.83%, which is 0.7% lower compared to the non-treated group for the same time period.

In the third model, that includes the Health & Containment index the adjusted R-square value is 0.6081. All four variables are significant on a 1%-level (P-value < 0.01), and all except the Group Fixed Effect are positive. The model implies that the pre-restriction monthly volatility for the non-treated group is 7.07%, and for the treated group, it is 6.2%. i.e., 14.03% lower than the non-treated group during this specific period. For the restricted time period, the non-treated group has a monthly estimated volatility of 22.5% and for the treated group it amounts to 22.51%, which is 0.04% lower than for the non-treated group.

The δ-parameter is positive and significant for all three models, which has the same indications as earlier presented models. Specifically, that the restriction seems to indicate that volatility increases, rather than decreases which was the purpose of the implementation of the short-selling restriction.

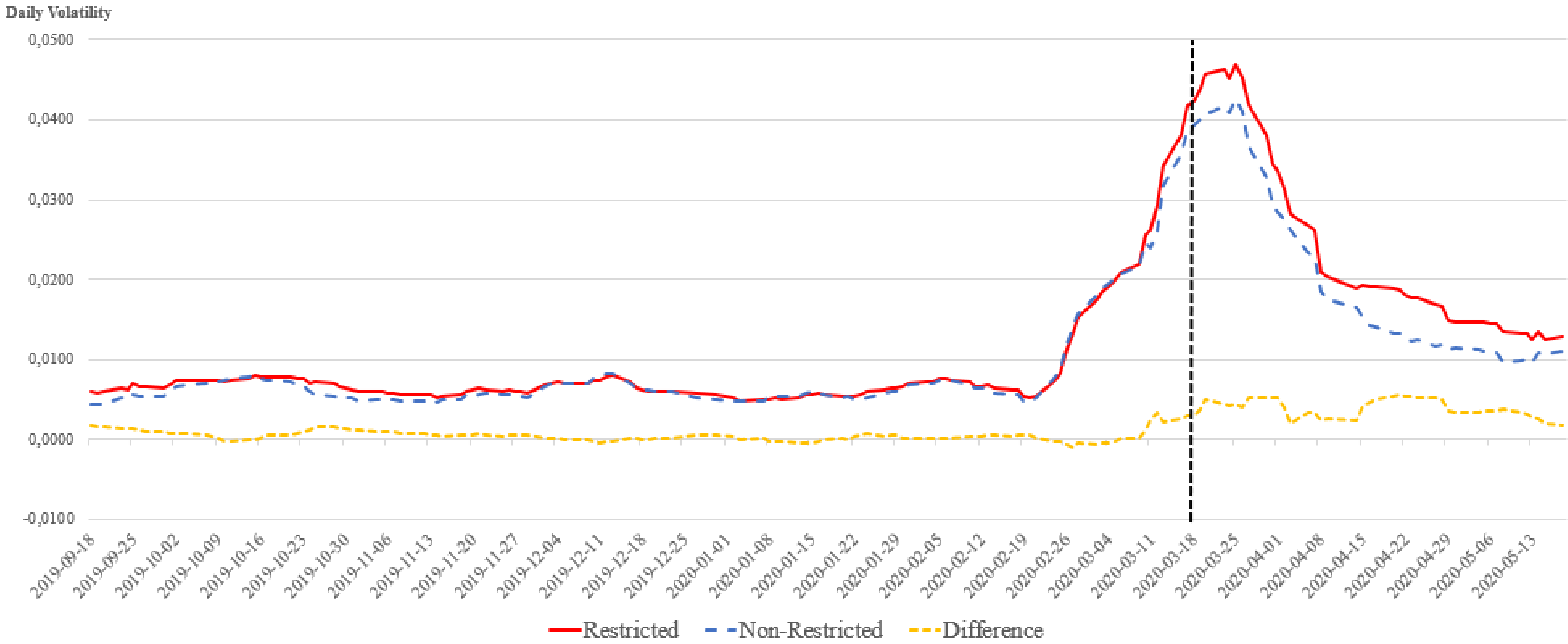
4.4 Validation of Results

4.4.1 Parallel Trends

4.4.1.1 Visual Inspection

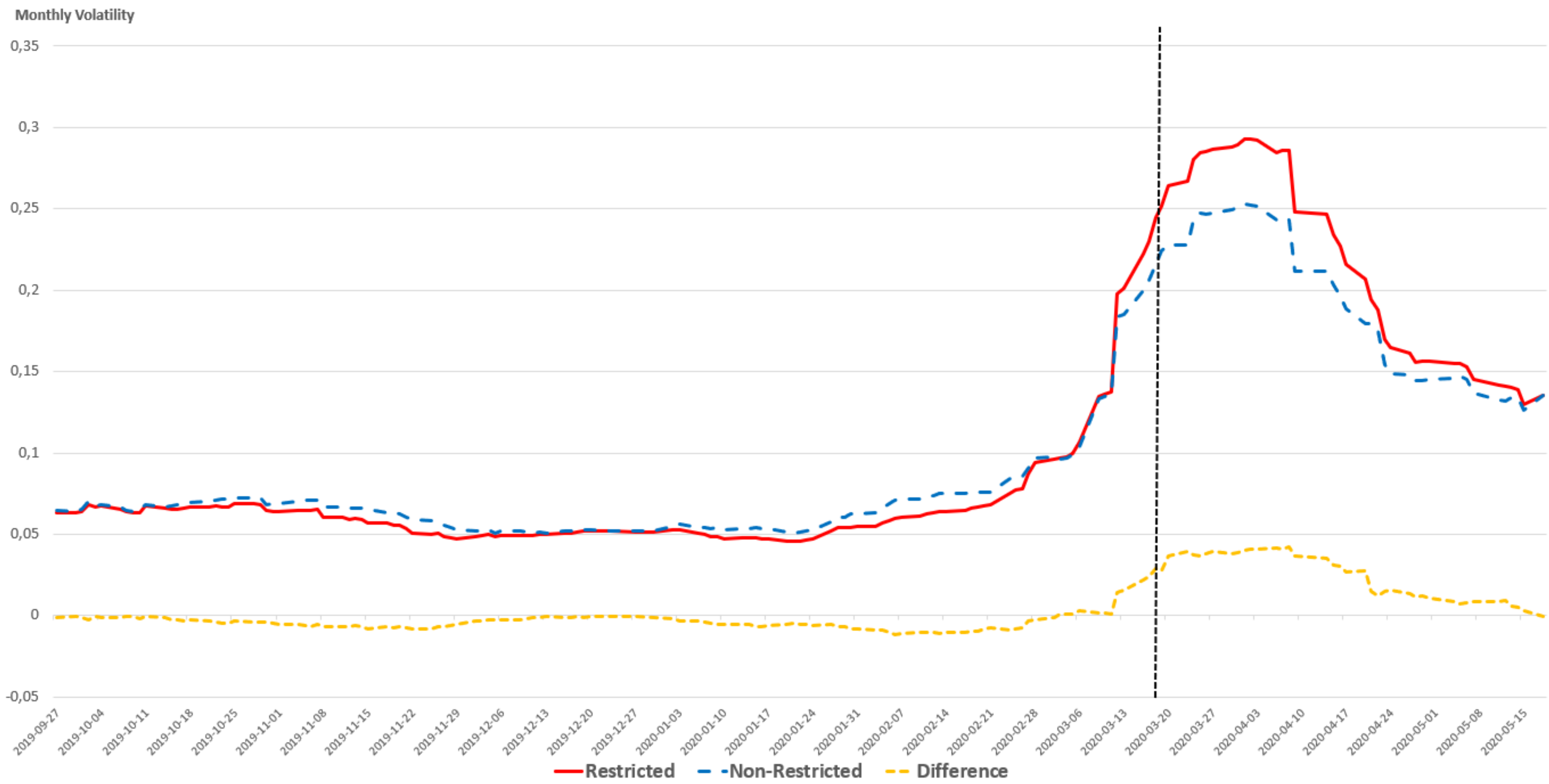
A visual representation of the daily volatility in Figure 1 and monthly realized volatility in Figure 2 and 3 for the restricted- and non-restricted group is presented below. For the index, the decomposed index and the financial sector, respectively. In all three figures it is visually clear that the two groups have no distinguishable trend difference in the pre-restriction period. Which is an indication that the parallel trend assumption is satisfied. However, the restricted group seem to have a higher volatility during the period where short-selling restrictions was introduced. This can be seen as the red line is consistently above or close to the blue line after the 18th of March 2020. Further, the yellow dotted line that represents the difference between the two groups is also noticeably higher post restriction than during pre-restriction. Moreover, this provides the same indication as the regression results. That is, the implementation of short selling restrictions tends to increase market volatility, instead of calming the market.

Figure 1 - Index Volatility, post and prior short-selling restriction



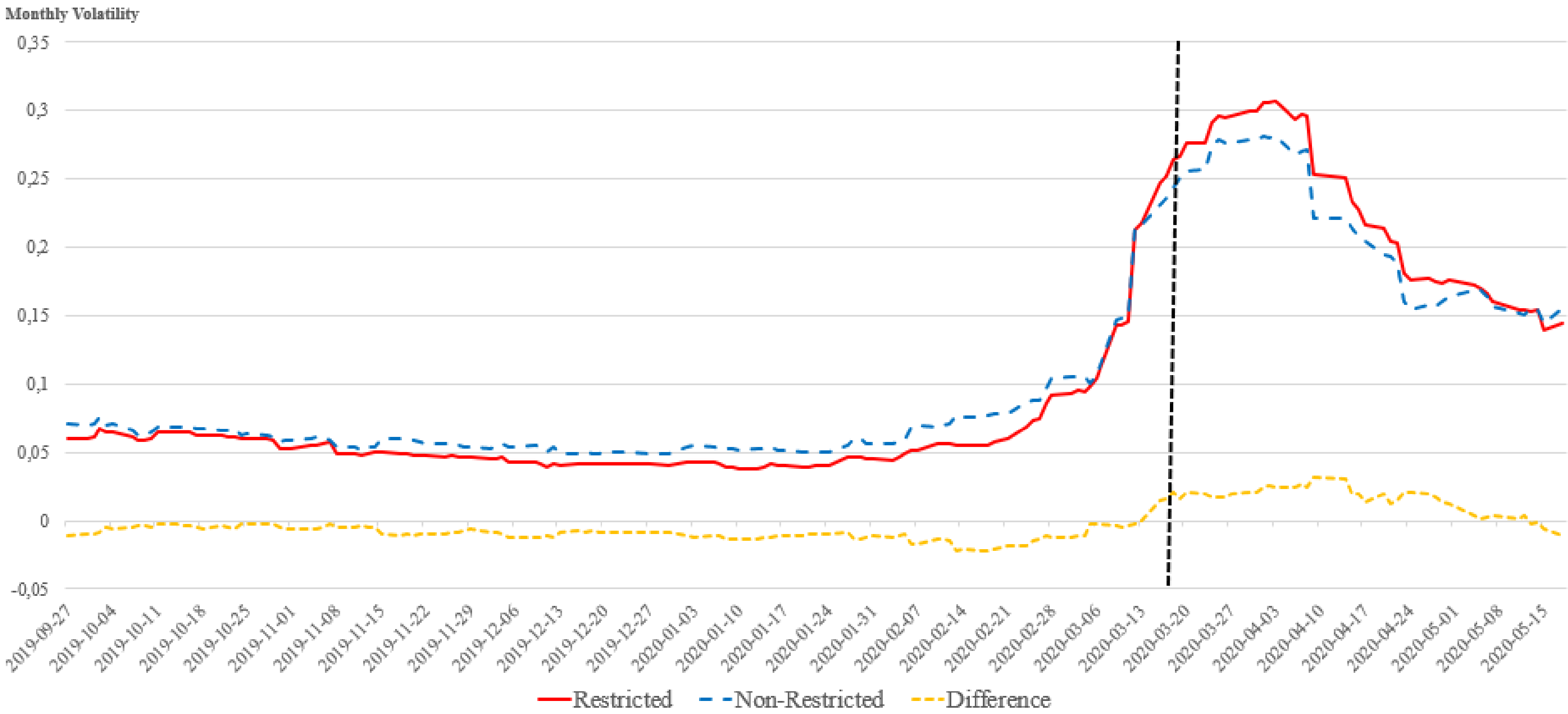
Note: Figure 1 illustrates the index group volatility, measured with the Garman-Klass estimator and a 10-day moving window. A vertical line is implemented on the 18th of March 2020 to represent the implementation of the short-sell restriction.

Figure 2 - Decomposed index volatility, post and prior short-selling restriction



Note: Figure 2 illustrates the decomposed index group volatility, measured with realized volatility and a 20-day moving window. A vertical line is implemented on the 18th of March 2020 to represent the implementation of the short-sell restriction.

Figure 3 - Financial Sector Volatility, post and prior short-selling restriction



Note: Figure 3 illustrates the financial sector volatility, measured with realized volatility and a 20-day moving window. A vertical line is implemented on the 18th of March 2020 to represent the implementation of the short-sell restriction.

4.4.1.2 Paired Sample T-test

Table 10 - Paired Sample T-test

Hypothesized Mean Difference: 0						
Parameter	Index		Decomposed Index		Financial Sector	
	Treatment Group	Control Group	Treatment Group	Control Group	Treatment Group	Control Group
Mean	0.0158	0.0179	0	0	0.0007	0.0008
Variance	0.0044	0.0061	0.0123	0.0119	0.0119	0.0127
t-stat	-0.7151		-0.0381		-0.0659	
P(T<=t) one-tail	0.2379		0.4848		0.4737	
P(T<=t) two-tail	0.4759		0.9696		0.9474	

Note: In Table 10, the results from the paired sample t-test is displayed for the three different approaches. The critical t-value is for the one-sided tail, 1.64 and for the two-sided tail 1.96 on a significance level of 5%.

The paired sample t-test is a formal statistical test that tests the difference in the average growth rate between two groups (Roberts & Whited, 2013). The test is performed with Equation 5, where the following hypothesis is applied:

H0: *No significant trend difference between the groups*

H1: *Significant trend difference between the groups*

The test fails to reject the null hypothesis for all three approaches since all three t-stats are below the different critical values and the corresponding P-values are above the different significance levels, which implies that there is no trend difference between the treatment group and the control group before treatment, i.e. before the short-selling restriction. Hence, both a visual inspection, and a formal paired sample t-test gives the indication that the parallel trend assumption is satisfied. Although, the tests are not enough to conclude that the assumption has been satisfied but it can be comforting in the validation of the assumption. Hence, implying that the results obtained are reliable.

4.4.1.3 Synthetic Control Group

A visual representation of the daily volatility estimated with the Garman-Klass estimator for the restricted- and non-restricted group are displayed in Figure 4 in the Appendix. The graph is similar to the graph displayed in Figure 1. However, it differs slightly since it by definition is created to fit the pre-restriction period with the objective to minimize the pre-restriction daily volatility difference between the control- and treatment group. Consequently, the visual representation of the trend difference in the pre-restriction period for the synthetic control group is even smaller than in the standard control group, displayed in Figure 1.

Table 11 - Base Regression Results with a Synthetic Control Group (Index)

Dependent variable: Volatility (Daily)		
No. Observations: 984	Adjusted R-Square: 0.35	Significance-F: 0 ***
Parameter	Coefficient	P-Value
α (Intercept)	0.0083	0 ***
	(0.0004)	
β (Time Fixed Effect)	0.0121	0 ***
	(0.0009)	
γ (Group Fixed Effect)	0.0002	0.71
	(0.0006)	
δ (Restriction Effect)	0.0037	0.0021 ***
	(0.0012)	

Note: Table 11 displays the results of the base difference-in-difference regression with a synthetic control group, where daily index volatility is a function of an intercept, time fixed effect, group fixed effect and the treatment effect which represents the restriction effect. The coefficients are in daily values, i.e., daily volatility. Details about what combination of parameters represents what are presented in Table 1. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to a P-Value that is assigned either *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05) it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed. The variables that are included in Table 11 are (1) Time Fixed Effect, that is a dummy variable that takes the value equal to 1 post implementation of restriction, (2) Group Fixed Effect, is a dummy variable that takes the value of 1 if the observation is included in the treatment group and 0 if it is in the control group, (3) Restriction Effect or Treatment Effect is a dummy variable that takes the value of 1 for observations that are in the Treatment group, post the restriction implementation.

In Table 11, the results for the base Difference-in-Difference estimator, with the use of a synthetic control group is displayed. The purpose for these results is to analyze if there is any noteworthy difference between these results and the results that were obtained using the standard control group. Since, this model is specifically created to satisfy the parallel trends assumption the results are reliable. The δ-coefficient has the P-value of 0.0021, which is strictly less than the P-value of 0.0041 that was obtained when using the standard control group, though both being significant on a 1%-level (P-value < 0.01). The magnitude of the δ-coefficient is slightly larger, 0.37% with the synthetic control group, compared to 0.35% with the standard control group. The γ-coefficient is notably different, with a coefficient value of 0.02%

connected to a P-value of 0.71, compared to the 0.05% and P-value of 0.41 that was obtained using the standard control group. However, this is in line with expectations since we create the synthetic control group, with the main objective to be as similar to the treatment group as possible for the pre-restriction period to satisfy the parallel trend assumption.

Table 12 - Modified Regression Results with a Synthetic Control Group (Index)

Dependent Variable: Volatility (Daily)			
Parameter	Model 1	Model 2	Model 3
α (Intercept)	0.0065***	0.0077***	0.0055***
	(0.0004)	*(0.0004)*	*(0.0004)*
γ (Group Fixed Effect)	0.0006	0.0004	0.0015***
	(0.0005)	*(0.0006)*	*(0.0005)*
δ (Restriction Effect)	0.0014	0.0008	0.0014
	(0.001)	*(0.0012)*	*(0.0009)*
Stringency	0.0036***	-	-
	(0.0002)		
Economic Support	-	0.0034***	-
		(0.0002)	
Health & Containment	-	-	0.0038***
			(0.0002)
Adj. R-Square	0.4862	0.4186	0.4876
No. Observations	984	984	984

Note: Table 12 displays the results of the modified difference-in-difference regression with a synthetic control group, where daily index volatility is a function of three different models. All three models include, an intercept (α), Group Fixed Effect (γ), Restriction effect (δ), while model one includes the Stringency index, model two, the Economical index and model three adds the Health & Containment index. Details about what combination of parameters represents what are presented in Table 1, with the exception of the index parameter. Standard errors are presented in *Italic* and a parenthesis below each coefficient. Each parameter coefficient is connected to *, ** or *** depending on its statistical significance level (Berger & Mortera, 1991). If the coefficient is significant on a 1%-level (P-value < 0.01), it will display three stars ***, whereas if it is significant on a 5%-level (P-value < 0.05), it will display two stars ** and lastly if the coefficient is significant on a 10%-level (P-value < 0.1), one star * will be displayed.

In Table 12, the results from the modified Difference-in-Difference estimator using a synthetic control group are displayed. The δ-coefficients are not significant on a 10%-level (P-value > 0.1) for any specification which is identical to the results that was obtained from the modified Difference-in-Difference estimation using the standard control group. The values of the δ-coefficients with the synthetic control group are 0.14%, 0.08% and 0.14%, for the Stringency-, Economic Support- and Health & Containment specification, respectively. Compared to the

0.13%, 0.06% and 0.14% that was obtained using the standard control group. As in the base Difference-in-Difference estimation, the notable difference in regression outputs is the γ-variable that represents the Group Fixed Effect. The γ-coefficient gets smaller for each specification. For the first specification, when including the Stringency index the γ-coefficient is no longer significant on a 10%-level (P-value > 0.01). This is again, in line with the expectations about the model. Since, the synthetic group is created to be similar to the treatment group in order to satisfy the parallel trend assumption.

5 Analysis & Discussion

In the following chapter, the results are analyzed with the help of the theories and previous studies that have been presented in this study. Initially, the results for the index approach are analyzed, and subsequently both the decomposed index approach and the financial sector approach are also analyzed.

The majority of our different research designs and model specifications confirm that introducing short selling restrictions in fact increases market volatility, which contradicts the stated purpose of the implementation of the ban, that it would calm the market and decrease the market volatility. This is consistent with the theoretical literature presented by Miller (1977) and Diamond and Verrecchia (1987). Since, both of these studies when taken together argue that the presence of short sellers helps informational efficiency in markets by allowing prices to reflect the intrinsic value of securities and increasing the speed of adjustment for prices to new information. In addition, they state that restrictions on short selling seem to reduce informational efficiency and therefore decrease the overall market quality. In other words, volatility would be expected to increase as a result of short-selling restrictions. However, regulators often refer to low volatility as a justification for implementing restrictions or bans on short-selling. Although, previous empirical research that has been conducted in this field (e.g., Alves, Mendes & Silva, 2016; Beber et. al., 2020; Beber & Pagano, 2013; Boehmer, Jones & Zhang, 2013; Bohl, Reher & Wilfling, 2016; Helmes, Henker & Henker, 2017) are consistent in their findings of a decrease in market quality as a result of short-selling restrictions. Specifically, a vast majority of the previous literature on the subject does not recommend an implementation of short-selling restrictions as they negatively affect market quality, i.e., liquidity, volatility and price discovery mechanisms, even in times of a crisis.

In the following sections, we will go through each of the three different approaches in detail.

5.1 Index Approach

The estimated δ-parameter that represents the restriction effect was estimated through a base Difference-in-Difference estimator, and with a modified Difference-in-Difference estimator that had three different specifications. Whereby, for both estimators and all three specifications the δ-parameter was a positive coefficient. However, for the modified Difference-in-Difference estimation the restriction effect, δ, was not significant on a 10%-level. The estimated coefficient for the δ-parameter were also consistently lower in the modified model compared to the base model. For the base model, the δ-coefficient was significant on a 1%-level (P-value

< 0.01) and took the value of 0.35%, while in the modified model, it took the values of 0.13%, 0.06% and 0.14% for the three different specifications. This can be explained by the replacement of the dummy variable, D_t, that represented the Time Fixed Effect with variables that contains more information, namely Stringency, Economical support and Health & Containment.

As the δ-variable experienced a decrease in coefficient value and its statistical significance level between the two models, it may indicate that the first model, the base Difference-in-Difference estimator has omitted variables problems. In other words, there are variables that explain the change in volatility for this approach that is not included in the specific model and therefore parts of the effect of the missing variables potentially affects the restriction effect. In our case, it makes it larger and more significant. However, we cannot conclude that this in fact is the problem for the index approach since this is the approach that has the fewest number of observations, specifically 984. Further, the volatility was modeled with the Garman-Klass Volatility Estimator which is not robust, in the sense that it does not consider the opening jump in index prices. The overnight jumps introduce a bias in the modeling of volatility (Fiszeder, 2013). Nonetheless, the positive sign of the coefficient, is in line with what earlier literature has concluded on, that the restriction has a contradictory effect on market volatility. However, as stated above the significant levels of these coefficients, and the nominal parametric values are not coherent between the base- and modified Difference-in-Difference estimators, where additional explanatory variables have been included.

The estimated volatility from the base Difference-in-Difference regression, displayed that the treated group had a volatility that was 6.25% higher than the non-treated group, prior to the short-selling restriction. However, after the implementation, the treated group had a daily volatility that was 19.7% higher, compared to the non-treated group. The volatility difference between the groups, during the event increased substantially. The Stringency specification in the modified Difference-in-Difference estimator displayed the same thing, that the difference in volatility between the two groups increased. The treated group had a volatility that was 1.45% higher in the pre-restriction period, while it was 8.5% higher during the restricted period.

However, the last two specifications, when we implemented an economical support- and a health and containment variable did not coincide with the two earlier models. The volatility difference between the treated- and non-treated group went from 9.4% and 34%, prior to the restriction, to a 5.6% and 11.36% difference during the restriction. Which implies that the volatility increased more in per cent for the non-treated group, compared to the treated group, during the restricted period. Which is contradictory to what the rest of our empirical results and previous literature concludes. However, it is line with the fact that the modified Difference-in-Difference estimator, with the Economical support and Health & Containment specification provided insignificant δ-coefficients for this specific approach.

The validation of the results for this approach is based on the parallel trends assumption. More specifically, that in the absence of treatment the treated companies and the control groups volatility should be affected by Covid-19 and other external events in the same way. However, it is not possible to formally test this assumption. Although, we applied three different methods that at least can be comforting in the validation of the assumption for the Index approach. Firstly, a visual inspection of Figure 1, to analyze if the trend looks similar in the pre-restriction period between the two treatment- and control group, which is satisfied. Secondly, a formal statistical paired sample t-test, that tests if the trend between two groups is significantly different from 0, which is also satisfied. Lastly, we introduced a synthetic control group to this approach. With the the objective to create a synthetic control group that is close to being identical to the treatment group in the pre-restriction period. The estimated δ-coefficient, displayed the same 1% significant level (P-value < 0.01), and similar values, 0.37% when using the synthetic control group, and 0.35% when using the standard control group. Since the synthetic control group and treatment group by construction is very similar in the pre-restriction period, the γ-variable received a higher p-value and lower coefficient value when using the synthetic control group. However, considering the similar regression outputs from the synthetic control group and standard control group, it gives the indication that the results that were obtained from the base Difference-in-Difference estimator with the standard control group are reliable.

Reaching back to the hypothesis of this study there are somewhat mixed results for this approach. However, for both estimators and all three specifications the δ-parameter was a positive coefficient and in the base Difference-in-Difference estimation the restriction effect, i.e., δ, was significant on a 1%-level (P-value < 0.01). One possible explanation for this could be the theory prediction made by Miller (1977) and Diamond and Verrecchia (1987), stating that the presence of short sellers helps informational efficiency in markets. Hence, restrictions on short selling reduce informational efficiency and therefore decrease the overall market quality, in this case, increases the volatility.

5.2 Decomposed Index Approach

The same methodology was applied for the Decomposed Index Approach, as the earlier Index approach with the difference that we modeled monthly volatility with Realized Volatility instead of daily volatility with the Garman-Klass volatility estimator. Two different Difference-in-Difference estimators, one base and one modified that included three different specifications was applied to the Decomposed Index. The δ-coefficient is still the parameter of interest to be able to analyze the isolated restriction effect.

For the base model, the δ-coefficient is a positive value of 2.79% and significant on a 1%-level (P-value < 0.01), which implies that the implementation of the short-selling restriction increases the monthly volatility of 2.79%. For the modified Difference-in-Difference, with the Stringency, Economic Support and Health & Containment specification the δ-coefficient takes the values of 2.26%, 1.34% and 2.36%, respectively. All of which are significant on a 1%-level (P-value < 0.01). The replacement of the Time Fixed Effect variable with a variable containing more information in this approach does not affect the significance levels, however the δ-coefficients are notably smaller in the modified version, which provides the indication that the different specifications remove explanatory power from the isolated restriction effect. The most notable change is when Economic Support is included as the specification since the δ-coefficient takes the value of 1.34%, versus 2.79% in the base model which is a difference of more than 50%. Restriction on short-selling can be seen as a financial instrument to reduce market volatility since it is directly applied to financial assets. These results give the indication that other financial government interactions rather than just short-selling restrictions are affecting market volatility to a large extent, like Economic Support. The drop in estimated δ-coefficient values for the modified Difference-in-Difference estimator compared to the base version, gives the same indications as the Index Approach. Namely, that the inclusion of variables that explain more than a dummy variable that represents a time fixed effect, does affect the δ-variable, in other words the restriction effect.

In similarity to the Index Approach, the validation of the results for this approach is based on the parallel trends assumption. We applied two necessary tests that at least can be comforting in the validation of the assumption. Both of them, namely, the visual inspection presented in Figure 2 and the paired sample t-test in Table 10, displayed similar indications. More precisely, that there is no trend difference between the treatment group and the control group before treatment, i.e., before the short-selling restriction. Hence, both gives the indication that the parallel trend assumption is satisfied, which imply that the obtained results are reliable.

Once again, reaching back to the hypothesis of this study, the δ-variable was a positive coefficient significant on a 1%-level (P-value < 0.01) for both models and for each respective specification. In contrast with the slightly more mixed results of the Index Approach, the results for this approach is unambiguous. This in turn, coincides with previous literature predicting that the presence of short sellers helps informational efficiency in markets. Moreover, restrictions on short selling reduce informational efficiency and therefore decrease the overall market quality, in this case the implementation of a short-selling restriction increases market volatility.

5.3 Financial Sector Approach

When examining the Financial Sector Approach, the same methodology was applied as for the earlier mentioned approaches. Equivalently, as in the case of the Decomposed Index Approach, we modeled monthly volatility with Realized Volatility. Further, the two different Difference-in-Difference estimators used previously are also applied for this approach. Consequently, the δ-coefficient is still the parameter of interest to be able to analyze the isolated restriction effect.

In the base model, the δ-coefficient is a positive value of 2.39% and significant on a 1%-level (P-value < 0.01). Thus, implying that the implementation of the short-selling restriction increases the monthly volatility of 2.39%. For the modified Difference-in-Difference, with the Stringency, Economic Support and Health & Containment specification the δ-coefficient takes the values of 1.75% significant on a 1%-level (P-value < 0.01), 0.74% significant on a 5%-level (P-value < 0.05), and 1.89% significant on a 1%-level (P-value < 0.01), respectively. These results are in line with the findings of the Decomposed Index Approach. Specifically, that the replacement of the Time Fixed Effect variable with a variable containing more information in this approach does not affect the significance levels. With the exception of the specification with Economic Support variable for which the significance level went from a 1%-level to a 5%-level. Moreover, the δ-coefficients are notably smaller in the modified version, which provides the indication that the different specifications remove explanatory power from the isolated restriction effect. The most noticeable change is, as in the Decomposed Index Approach, when the Economic Support is included as the specification. Since, the δ-coefficient takes the value of 0.74%, versus 2.39% in the base model which is about 69% lower. These results are in line with what we found in the Decomposed Index Approach and they give an indication that other financial government interactions rather than just short-selling restrictions are affecting market volatility to a large extent, like Economic Support. Furthermore, as for both of the other approaches the drop in estimated δ-coefficient values for the modified Difference-in-Difference estimator compared to the base version indicates the same thing. Namely, that the inclusion of variables that explain more than a dummy variable that represents a time fixed effect, does affect the δ-variable, in other words the restriction effect.

In similarity, to the Decomposed Index Approach, the validation of the results for this approach is based on the parallel trends assumption. Once more, we applied two necessary tests that at least can be comforting in the validation of the assumption. Both of them, namely, the visual inspection presented in Figure 3 and the paired sample t-test in Table 10, displayed that there is no trend difference between the treatment group and the control group before treatment, i.e., before the short-selling restriction. Thus, both gives the indication that the parallel trend assumption is satisfied, which imply that the obtained results are reliable.

In order to reach back to the hypothesis of this study, the δ-variable was a positive coefficient significant on a 1%-level (P-value < 0.01) for both models and for each respective specification besides the Economic and Support specification which was significant on a 5%-level (P-value < 0.05). In line with the Decomposed Index Approach, this approach also exhibits unambiguous results. Consequently, the results coincide with previous literature predicting that the presence of short sellers helps informational efficiency in markets. Moreover, restrictions on short selling reduce informational efficiency and therefore decrease the overall market quality, in this case the implementation of a short-selling restriction increases market volatility. However, we find no clear significant evidence that the financial sector is more or less affected compared to the remaining market. This may stem from the fact that the 2020 short-selling restrictions was a consequence of a pandemic and not a financial crisis, which has been the case for previous restrictions.

6 Conclusion

In the following chapter, the conclusions of the study are presented based on the results of the applied tests and the analysis with regard to the research hypothesis of this study.

The purpose of this study was to examine if the stated reason for the implementation of the short-selling restrictions by regulators on the 18^{th} of March 2020 during the Covid-19 crisis actually achieved a decrease in volatility on the banned stocks. In order to do so, we investigated the hypothesis outlined in this study and analyzed the results given by the applied tests and method in the previous chapters. The hypothesis that was developed based on the theoretical framework is as follows:

The short-selling restrictions during the Covid-19 pandemic did not have an impact on the reduction of volatility

Three different approaches were used to examine the impact that the short-selling restriction had on volatility. Namely, an Index Approach, a Decomposed Index Approach, and a Financial Sector Approach. All of the approaches exhibited analogous results regarding the short-selling restrictions impact on volatility. For all three approaches and their respective specifications of the models, the δ-variable that represents the restriction effect, was a positive coefficient. Moreover, the δ-variable was significant in all base models and in all modified regressions, except for the Index approach. Implying, that the implementation of the short-selling restriction increased market volatility in a range of between 0.06 and 0.37% on a daily basis and 0.74 to 2.79% on a monthly basis, depending on the model and specification. Furthermore, an inclusion of additional variables containing more information than the Time Fixed Effect variable was performed. The results indicated that other financial government interactions rather than just short-selling restrictions are affecting market volatility to a large extent, for example Economic Support.

Regulators often refer to low volatility as a justification when implementing restrictions. Interestingly, however, previous literature does not recommend implementations of short-selling restrictions as they negatively affect market quality, i.e., liquidity, volatility and price discovery mechanisms, even in times of crisis. The findings of this study are aligned with the results of previous studies, and we also argue that an implementation of short-selling restrictions is not recommended if the stated purpose of it refers to a reduction of volatility. There are, however, other possible reasons for regulators to impose such restrictions. Possibly, there might be political reasons or political pressure on the regulators. Further, interestingly, no country imposed a ban during the more severe second Covid-19 wave, this is also pointed out by Bessler and Vendrasco (2020).

Our findings contain informational value for investors, regulatory actors and academics. In order to gain deeper insights of the effect that short-selling restrictions have on volatility during turbulent times on the market. Further, it is of major importance for regulators to gain knowledge of the effects, this enables them to assess the reasoning behind future implementations.

Further research related to this topic could be to conduct a study rather on the incentives and arguments of regulators on the implementation of the restrictions. Since, the vast majority of studies over several different crises has found that regulators failed to achieve the goals of the implementation of the short-selling ban. Regardless, however, regulators still seem to end up implementing them in times of financial crisis, possibly as a result of them facing a strong political pressure to appear to be doing something about the crisis. Another potential topic, deriving from the findings of this study, is to include a wider range of variables, that could potentially explain the change in market volatility and remove the explanatory power of the variable that represents the restriction effect.

7 Reference

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8 Appendix

Table 13 - Summary of Previous Studies

Authors	Crisis	Sample	Conclusions
Boehmer, Jones & Zhang (2013)	Financial	727 banned financial stocks in the United States and 727 non-banned stocks	Regulators failed to achieve the goals of the implementation of the short-selling ban
Beber & Pagano (2013)	Financial	16 491 stocks from 30 countries (Most European markets and developed non-European markets)	Conclusions summed up by quote of former SEC chairman stating that in hindsight they would not impose the restrictions again
Bohl, Reher & Wilfling (2016)	Financial	An index constructed by 10 banned stocks on the German DAX-index and control group of the remaining non-banned stocks	Found a destabilizing impact of short selling constraints on the volatility of stock returns Recommend regulators not to impose short-selling restrictions to solve for this problem
Helmes, Henker & Henker (2017)	Financial	Treatment group of 45 financial stocks in Australia and control group of 45 in Canada	Stated goal of calming the market was not achieved by regulators
Alves, Mendes & Silva (2016)	Eurozone	170 financial stocks (58 treatment group) in France, Belgium, Spain and Italy	Regulators failed to reduce volatility with applied measures
Beber et. al (2020)	Financial & Eurozone	13 473 stocks in financial and 16 424 stocks in Eurozone crisis. Data from 25 countries that cover all main developed countries	The evidence indicates that the results are particularly significant for banks. Short-selling bans are not associated with greater bank stability
Bessler & Vendrasco (2020)	Covid-19	Two samples of which the first is 175 banned and 175 non-banned stocks and the second 350, respectively France, Italy, Spain, Belgium, Austria and Greece included in the treatment group	Introduction of short-selling bans for market quality reasons are not justified
Siciliano & Ventoruzzo (2020)	Covid-19	1 356 stocks from 14 EU countries and the UK from three temporary bans. The treatment group was 242 banned stocks	Short-selling bans during market crises lack effectiveness and have negative consequences on market quality

Table 14 - List of CIGS sectors in respective country

Country GICS Sector	Austria	France	Belgium	Germany	Netherlands	Sweden	Treatment (Average)	Control (Average)
Energy	2 (0.1)	0 (0)	0 (0)	0 (0)	1 (0.04)	0 (0)	(0.03)	(0.01)
Industrials	4 (0.2)	11 (0.30)	1 (0.06)	3 (0.11)	1 (0.04)	10 (0.35)	(0.19)	(0.17)
Consumer staples	0 (0)	4 (0.11)	2 (0.13)	2 (0.07)	2 (0.09)	1 (0.03)	(0.08)	(0.06)
Financials	5 (0.25)	4 (0.11)	5 (0.31)	4 (0.14)	6 (0.26)	6 (0.2)	(0.22)	(0.2)
Communication services	1 (0.05)	0 (0)	2 (0.13)	1 (0.04)	3 (0.13)	3 (0.1)	(0.06)	(0.09)
Materials	3 (0.15)	1 (0.03)	1 (0.06)	3 (0.11)	4 (0.17)	3 (0.1)	(0.08)	(0.13)
Consumer Discretionary	0 (0)	8 (0.22)	0 (0)	5 (0.18)	1 (0.04)	2 (0.07)	(0.07)	(0.1)
Health Care	0 (0)	2 (0.05)	1 (0.06)	4 (0.14)	2 (0.09)	2 (0.07)	(0.04)	(0.1)
Information Technology	1 (0.05)	5 (0.14)	1 (0.06)	2 (0.07)	2 (0.09)	2 (0.07)	(0.08)	(0.08)
Utilities	1 (0.05)	1 (0.03)	0 (0)	2 (0.07)	0 (0)	0 (0)	(0.03)	(0.02)
Real Estate	3 (0.15)	1 (0.03)	3 (0.19)	2 (0.07)	1 (0.04)	0 (0)	(0.12)	(0.04)
Total No. Obs	20 [0]	37 [3]	16 [4]	28 [2]	23 [2]	29 [1]	153 [12]	

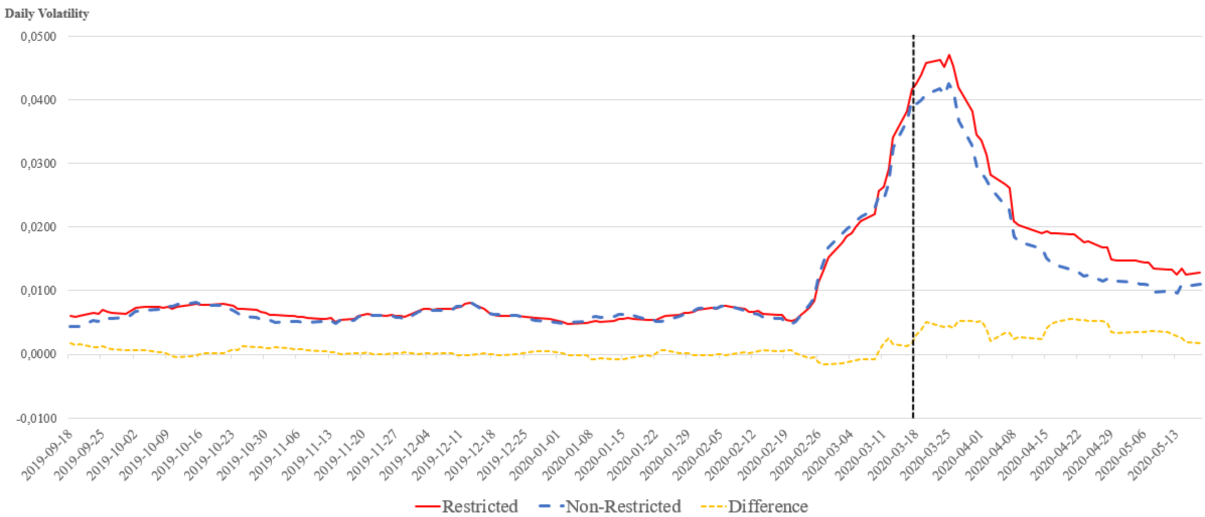
Note: In table 14, the distribution of the different CIGS in the different countries is displayed with the percentage in parenthesis as decimals. The average distribution of the sectors in the treatment group and control group is displayed in the two most right columns, to visually display the similarities between the two groups. The numbers in the squared brackets represents the number of stocks that have been excluded.

Table 15 - Variance Inflation Factor

Parameter	VIF
Beta	567
Gamma	1.06
Delta	2.3
Economic Index	149
Health and Containment index	2 945
Stringency Index	1 909

Note: The VIF is created by running a regression where each explanatory variable, is explained by the other explanatory variables. The threshold for the VIF is set to 10, where if it is above this value, it will cause severe multicollinearity in the model.

Figure 4 - Daily Volatility for Index Approach with synthetic control group



Note: Figure 4 illustrates the index group volatility, measured with the Garman-Klass estimator and a 10-day moving window. A vertical line is implemented on the 18th of March 2020 to represent the implementation of the short-sell restriction. This is with a synthetic control group.