MASTER THESIS

The impact of COVID-19 on share prices across different sectors within the US stock market

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Abstract

The purpose of this study is to identify whether the sectors on the US stock market have perceived significant abnormal stock returns during the COVID-19 period. To execute this, a market model event study has been conducted. The sample consists of companies from the NYSE and the NASDAQ, and the sectors are retrieved from the Orbis data base and consist of a total of 28 BvD sectors. After deleting the missing data, a final sample size of 4112 remains. Since COVID-19 has not one clear event date, four different events have been analysed: The first COVID-19 patient in the US (January 21, 2020), the US declares a public health emergency (February 3, 2020), the WHO declares a pandemic (March 11, 2020) and the Federal Reserve pledges to support the economy (March 23, 2020). Moreover, 3 event windows ([-3,3], [-5,5], [-10,10]) per event have been analysed to take pre-event leakage and delay in response time into consideration. The results show that the first three events experienced average negative abnormal returns, however, the third event has the strongest decrease: -11.5% [-3,3] and -21.7% [-5,5]. Contrary to this, the stocks experienced positive returns during the fourth event window: +7.0% [-3,3] and +1.2% [-5,5]. This indicates that the Behavioural Finance theory is applicable, since the stock market reacted positive during the fourth event, even though the seriousness of the COVID-19 virus has not changed. For the sectoral returns, there are nine sectors which have experienced significant negative abnormal returns during the first three events: Banking Insurance and Financial Services (BIFS), Transport, Fright & Storage (TFS), Travel, Personal & Leisure (TPL), Business Services (BS), Metals & Metal Products (MMP), Mining & Extraction (ME), Textile & Clothing Manufacturing (TCM), Property Services (PS), and Wholesale. By comparing these impacted sectors to the sectoral returns of previous pandemics, investors can learn from the market reactions for future pandemics.

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1. Introduction

1.1 Background

The COVID-19 pandemic is a recent, but continuing problem across the world. The first signs of the COVID-19 virus were announced on December 31, 2019, from Wuhan, China[1]. Soon after, on January 21, 2020, the first COVID-19 patient was discovered in the United States[2]. One year later, in January 2021, the total number of COVID-19 infections was around 85 million, of which over 20 million were confirmed within the United States[3].

COVID-19 has not only affected human health, but also the financial markets. Many countries introduced both life and work restrictions, also in the United States[4]. Especially in the first phase of the COVID-19 pandemic outbreak, the stock markets experienced a substantial decrease. When focusing on the two large American stock indices: The S&P500 index[5] and the Dow Jones Industrial Average[6], a decrease in share prices is perceived as of February 2020. The all-time low of the year 2020 for both indices are observed on March 23, 2020. This is the same day, the Federal Reserve pledged to support the economy, by any means necessary[7].

None withstanding, how can the individual investor learn from this significant decrease between February and March 2020? Are all sectors impacted equally? Or are there specific sectors that appear to be more or less affected than others? Figure 1 provides global index value changes from January 2020, until March 18, 2020 . This figure provides a clear overview and displays that some countries were stronger affected than others. This difference between countries is presumably caused by how severe the countries were affected by COVID-19, and what kind of governmental measures and restrictions were implemented by those countries. However, when

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1WHO (April 27, 2020). https://www.who.int/news/item/27-04-2020-who-timeline---covid-19

2 Schumaker (September 22, 2020). Timeline: How coronavirus got started. https://abcnews.go.com/Health/timeline-coronavirus-started/story?id=69435165

3 JHU (2020). https://coronavirus.jhu.edu

4 Our World in Data (2020). https://ourworldindata.org/policy-responses-covid

5 Investing.com (2020). https://www.investing.com/indices/us-spx-500-historical-data

6 Investing.com (2020). https://www.investing.com/indices/us-30

7 Casselman (March 23, 2020) https://www.nytimes.com/2020/03/23/business/economy/federal-reserve-how-rescue.html

studying more closely, the S&P500 experienced a stronger decrease (-10.6%) than the NASDAQ100 (-7.4%). Since both are US indices, this difference in decline cannot be explained by country-specific factors. Therefore, other factors appear to have influenced the strength of the share price decline during COVID-19 as well. To start identifying other possible factors, this paper will focus on the industry-specific factors since there appear to be sectors that have benefited more from COVID-19 than others. For instance, the food delivery revenue of platforms increased by 31.5% in 2020 compared to 21.5% in 2019[8]. Moreover, the video game sales increased as well, by 63% as of March 2020[9]. Another sector that has been positively impacted by the COVID-19 outbreak is the pharmaceutical industry.

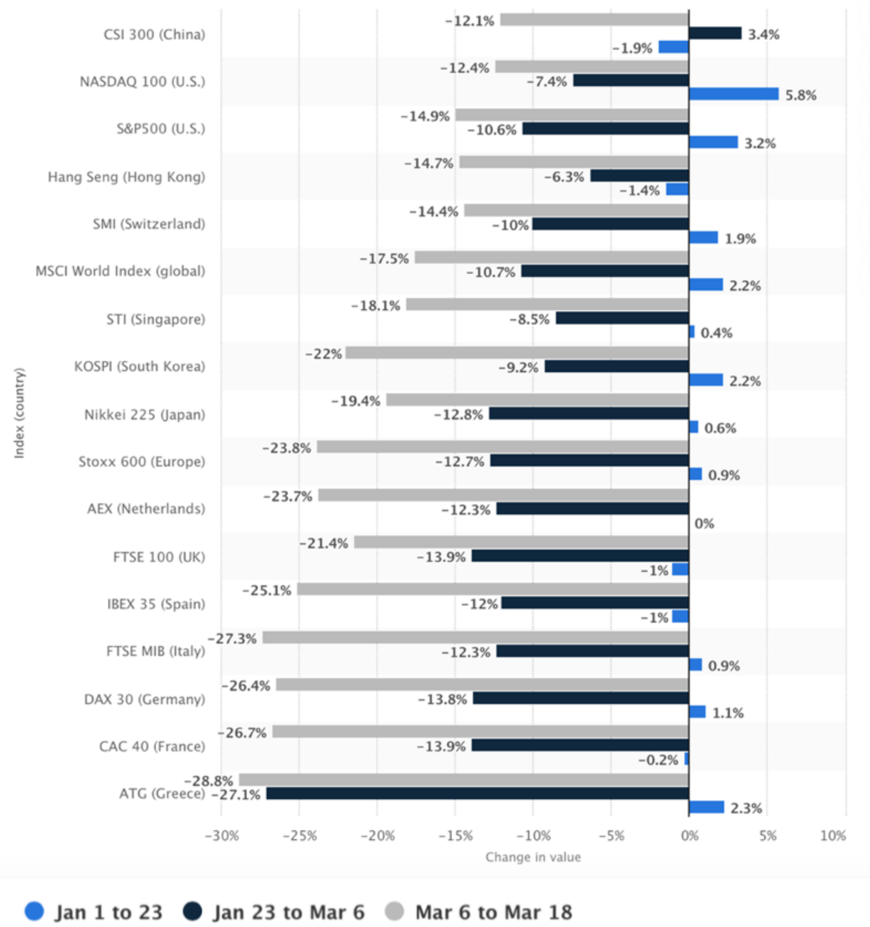

Figure 1: Change in value during coronavirus outbreak of selected stock market indices worldwide from January 1 to March 18, 2020[10]

[8] Statista (2020). *Online Food Delivery worldwide. https://www.statista.com/outlook/374/100/online-food-delivery/worldwide#market-globalRevenue*
[9] Statista (2021). *COVID-19: global video game sales increase as of March 2020. https://www.statista.com/statistics/1109977/video-game-sales-covid/*
[10] Statista (2020). https://www.statista.com/statistics/1105021/coronavirus-outbreak-stock-market-change/

1.2 Research question

To support the individual investor with the evaluation of their investment decisions and future decision making, the goal is to identify which sectors had significantly different share price changes during COVID-19 compared to the market. To study this, the following research question has been composed:

"How are firms across different sectors on the US stock market impacted by COVID-19?"

1.3 Theoretical and practical contributions

This paper will provide both theoretical and practical contributions. First, the practical contributions. Pandemics are a reoccurring phenomenon and have an impact on the financial market. Although that every pandemic has its own characteristics based on the nature of the pandemic, there also appear to be similarities. Once an investor is able to recognize the similarities and evaluate the historical pandemics, it could help the investor for future decision making. Based on the nature of COVID-19 and existing literature on past pandemics, I expect that specific industries have experienced a significant increase in share prices, whereas other sectors have experienced a significant decrease. Once these sectors have been established in this paper, investors may learn from this and apply the knowledge during a following pandemic.

Second, the theoretical contributions. Even though there is existing literature that covers the effect of COVID-19 on the stock market, there is limited research available regarding the effects on the different sectors. I have only found a few papers covering the effect of the COVID-19 on the different sectors in the stock market and only one covering the United States (Goodell & Huynh, 2020). That research however, only covered the cumulative abnormal returns for the event date February 26, with an event window of maximum 2 days. Since the duration of COVID-19 is significantly longer, and different governmental restrictions and support programs have been setup and changed since February 26, it is desired to investigate other time frames as well, including a more long term perspective.

1.4 Outline

A short outline of this Master Thesis Part II will be provided. The second chapter will consist of a theoretical framework. Four theories which could explain the effect of COVID-19 on the different sectors on the US stock market will be highlighted and discussed. Next, in the third chapter existing literature has been reviewed. This literature review consists of three main elements. First, the literature regarding the general determinants of a stock price will be reviewed. Then, the past exogenous events will be examined. Finally, existing literature regarding the effect of COVID-19 on stock prices will be analysed and hypotheses have been created.

2. Theoretical Framework

To identify which theory possibly could explain the effect of COVID-19 on the stock market, in the following section, four theoretical frameworks are outlined and discussed. The first three theories are commonly found in literature regarding stock market changes. The final theory was found in literature regarding COVID-19. First, the efficient market theory will be discussed, second, the random walk hypothesis will be outlined, third, the behavioural finance theory is highlighted, and finally, the black swan event theory will be discussed.

2.1 Efficient market theory

Starting with the efficient market theory. Fama (1970) defines an efficient market as a market in which all available information is entirely reflected in the share prices. So, a market where all investors act rational and share prices are up to date and reflect their true value.

Additionally, this efficient market theory can be subdivided into three distinct forms: weak efficiency, semi-strong efficiency and strong efficiency (Brealey, Myers, & Allen 2020). First, within weak efficient markets, the share prices only consolidate historical prices, whereas in semi-strong efficient markets, the share prices reflect all public information available, including media and press. Finally, within strong efficient markets, the share prices cover all information, both private and public (Brealey et al., 2020). So, this would suggest that there are no investors which can benefit from private information and from arbitrage trading (Jula & Jula, 2017). The strong efficient model however, is considered extreme and is not expected to represent the real-life market (Fama, 1970).

Fama, Fisher, Jensen, and Roll (1969) define the market efficient when share prices reflect all information promptly. However, how can this efficient market theory be measured. To measure the efficient market hypothesis, an assessment should be created on how new available information will be reflected in the share prices (Fama, 1970). This is usually measured by implementing the event study of abnormal returns (Brealey et al., 2020). The simplest method of abnormal returns are measured by subtracting the actual returns of a specific company during a specific event period from the market index. According to the efficient market hypothesis, on the event day and the day after, the stock prices should adjust according to the new available information, but after that, the price should remain stable (Brealey et al., 2020).

Existing research has tested whether the market during the COVID-19 period has been acted efficient. Vasileiou, Samitas, Karagiannaki, and Dandu (2021) have divided the COVID-19 timeline into five distinct periods. They find that the share prices had a normal return during the first two periods, until February 21st 2020. This indicates that the share prices do not immediately reflect all available information and since the Health Emergency had already been declared on the 30th of January, 2020, this could indicate as well that investors have underestimated the health risks of the virus (Vasileiou et al., 2021). After that, in the third and fourth period, the market experienced a rapid decline until the 18th of March 2020. Now, it appears that the stock market is reflecting the available information, however with a delay. Thus, investors start acting rational again. Nevertheless, in the fifth period, after the declaration of the relief program by the Federal Reserve, the share prices start to grow again, even though the COVID-19 virus still endangers the health and society (Vasileiou et al., 2021). This again could indicate that investors underestimated the current health risk and only consider the latest, positive information available. So, since the share prices during COVID-19 do not immediately reflect all information, Vasileiou et al. (2021) reject the efficient market hypothesis during COVID-19.

To summarize, this available literature suggests that the efficient market hypothesis is not applicable during the event of COVID-19. This means that not all the information available is reflected in the share prices. Next, the Random walk hypothesis will be explained.

2.2 Random walk hypothesis

The second theory is the random walk hypothesis, which is similar to the efficient market theory but has some fundamental differences. Both claim that investors cannot beat the market, but whereas the efficient market theory claims that the share prices "perfectly" reflect all available information, the random walk hypothesis claims that share prices cannot be predicted based on the available information, but rather take a random walk around the intrinsic value (Fama, 1995). In addition, Malkiel (1996) provides the following definition of a random walk, specifically focused on the stock market: *"A random walk is one in which future steps or directions cannot be predicted on the basis of past actions. When the term is applied to the stock market, it means that short-run changes in stock prices cannot be predicted."* So, that random walk hypothesis cannot be predicted based on past and present information.

According to Fama (1995), there are two techniques which may help to predict share prices in a random walk model, even though the essence of the random walk theory, is that it is not predictable. First, the chartist technique, which claims that past patterns in stock prices, so not historical information but patterns, may predict future patterns (Fama, 1995). So there appears to be a sequence between patterns in the past and future. The second technique is the theory of fundamental or the intrinsic value analysis. This technique claims that there are fundamental factors that can predict the intrinsic value of a stock, for instance the earnings, the industry and the economy (Fama, 1995). By comparing the share price to its intrinsic value, a possible prediction could be made (Fama, 1995).

Existing literature already focusses on COVID-19 and the random walk hypothesis. For instance, Dias, Heliodoro and Alexandre (2020) research the random walk hypothesis for the financial markets of Indonesia, Malaysia, the Philippines, Singapore, Thailand and China during the COVID-19 pandemic. They find that by implementing a non-parametric variance ratio test from January 2019 to July 2020, the stocks show correlations. This means that prices can be predicted based on historical price patterns, and thus were not random. Accordingly, the random walk hypothesis was rejected for all five countries (Dias et al., 2020). Moreover, Aslam, Mohti and Ferreira (2020) studied the intraday index from January 1st, 2020 to March 23rd, 2020 in eight European stock markets during the COVID-19 pandemic. They find that by applying a multifractality detrended fluctuation analysis, that multifractality is presence among these eight European stock markets, thus a pattern is recognized and therefore the random walk hypothesis was rejected (Aslam et al., 2020).

To conclude both studies have rejected the random walk hypothesis for the period of the COVID-19. This could indicate that during COVID-19, the stock market did not change randomly, and share prices could be explained by historical data and information in the market.

2.3 Behavioural Finance Theory

Within behavioural finance, the social and psychological aspect of the investor's decision making is researched, and how this may affect the share prices (Shiller, 2003). This is somewhat opposite from the efficient market theory. Whereas the efficient market theory expects investors to act rationally, the behavioural finance theory assumes that investors can also respond irrationally (Shiller, 2003).

These irrational investors can act and trade in two distinct ways, overconfident or conservative. Overconfident investors estimate the success rate of a company higher than it is, and believe to have better judgement than the regular investor (Brealey et al., 2020). So, when the majority of the investors trade in an overconfident manner, demand increases, share prices will raise above their intrinsic value, and will thus be overvalued (Brealey et al., 2020). Conservative investors on the other hand, often stay with their initial beliefs and thoughts, even though evidence proofs otherwise, so, new investment opportunities are often passed or reacted on too late (Brealey et al., 2020). This could cause undervaluation. This investor bias can be caused or influenced by many factors, two factors which are predominant in literature will be elaborated for the purpose of this research: risk perception and investor sentiment.

2.3.1 Risk perception

First, risk perception. Investors have different attitudes towards risk. For instance, some people enjoy to gamble, whereas other prefer to play safe. Three different types of risks are distinguished: risk averse, risk neutral and risk seeking (Lovric, Kaymak, & Spronk, 2008). Whether investors are risk averse or risk seeking, can depend on demographic factors like gender and age, but also on the investment horizon, which determines the time between the initial investment and the return. (Lovric et al., 2008). Nevertheless, trading in a risk averse or risk seeking manner is not only influenced by a person's personality, but is also influenced by past performance. For instance, investors who recently have generated profits, are more likely to take higher risk and trade (over)confident, whereas investors who have experienced some recent losses are more likely to avoid additional risk and thus act more conservative (Brealey et al., 2020). In turn, the risk perception of investors determine the level of irrational behaviour.

2.3.2 Investor sentiment

Another factor that influences the level of irrational behaviour of investors is investor sentiment. Brealey et al. (2020) outline that investor sentiment can influence the stock price changes. Investors can be bullish or bearish. Bullish indicates the believe that the share prices will increase, so being optimistic. Bearish on the other hand, indicates the believe that share prices will decrease, so being pessimistic (Brealey et al., 2020). Being either optimistic or pessimistic is driven by for instance anxieties, mood and the amount of fear (Ichev & Marinč, 2018). This is not only determined by the personality of a person, but may be influenced by external factors like the media as well. As an example, Tetlock (2007) studied the effect of media content on the US stock market returns and found that frequent pessimism in the media positively influences the conservative behaviour of investors and therefore predicts a decrease in stock prices. Similarly, Ichev and Marinč (2018) found that pessimism driven by the media did negatively influence investor sentiment and thus investment decision making during the SARS outbreak, which resulted in declined prices.

Studies conducted on COVID-19 and behavioural finance theory, resulted in similar outcomes. Vasileiou (2021) studied the relation between the fear index and the stock market changes. The results show that when the amount of fear increased in March 2020, the market declined. However, when the fear index decreased simultaneously with the introduction of the government support packages, the market started growing again (Vasileiou, 2021). This market change could thus be explained by the behavioural finance theory. Furthermore, Reis and Pinho (2020) find that the US investors demonstrated irrational investment behaviour during the COVID-19 pandemic by comparing whether a sentiment index or the amount of cases better predict the stock return. The efficient market hypothesis was thus rejected since the sentiment index better predicted the stock return during COVID-19 in the US. In addition, in the US, the tourism and real estate sectors were the most sensitive sectors to negative news (Reis & Pinho, 2020).

In conclusion, based on past research, there appears to be evidence that the market changes during the COVID-19 pandemic can be explained with help of the behavioural finance theory.

2.4 Black Swan Events

Finally, a black swan event will be described. Since a black swan event is perceived an event with a high impact, it is extremely influential, whether COVID-19 can be perceived as a black swan event and whether investors then act rationally (efficient market theory or random walk) or irrationally (behavioural finance theory), and learn from its impact on the overall stock market.

A black swan event has been described by Taleb (2007) and consists of three main elements. First, the event should be unforeseen, unlikely to occur. Second, the event has a tremendous impact, it will never be the same as before the event occurred. Finally, after the event has been analysed and clarified, it appears to be not as unpredictable as that may have seen before. The term, Black Swan event, originates from the story of a Dutch explorer who witnessed black swans in Australia (Taleb, 2007). Only white swans are found in Europe, so the European citizens imagined that something like a black swan would be impossible to exist, until a Dutch explorer witnessed a black swan in Australia. Now people are aware that black swans exist, it is considered to be logical, and actually bizarre that the European population imagined it as something impossible. Taleb (2007) describes examples of black swan events like the September 11 attacks, the dotcom bubble and World Wars I and II.

Considering these elements, a black swan event could be applied to the COVID-19 pandemic. The world population had not expected that a new virus would be able to spread this quickly and impact the world drastically. The impact from the event is extremely serious, for instance, the travel restrictions and lockdowns all over the world. And, after analysing the event, it seems sensible that a virus would arise in an overpopulated world, and spread quickly in a world where travelling is perceived as rather normal. Morales and Andreosso-O´Callaghan (2020) also describe COVID-19 as a black swan event. Nevertheless, others question whether COVID-19 can really be considered a black swan event. For instance, Goodell (2020) describes the COVID-19 pandemic as foreseeable, since global pandemics have been predicted numerously. Moreover, labelling COVID-19 as a black swan event may result in the perception that it is highly unlikely that something similar will occur repeatedly and therefore less time will be consumed on analysing the event and prevent future occurrence (O'Donnell, Shannon, Sheehan (2021)

So, whether COVID-19 can be considered a black swan event is inconclusive, however, evaluating the risks and effects is desired either way.

3. Literature Review

In the following section, existing literature will be discussed. First, the general determinants of share prices will be discussed, specifically, the firm-specific and the macro-economic variables. Secondly, the past exogenous events that have, or have not affected the stock market will be outlined. Finally, the existing literature regarding the effect of COVID-19 on the stock market will be considered.

3.1 Share price determinants

First, it is desirable to understand how share prices are determined, without considering COVID-19. This information may help to understand the share price changes during the COVID-19 event. This information can also be applied to determine explanatory variables by controlling whether third variables may explain the results. Both the firm-specific variables and the macroeconomic variables will be discussed.

3.1.1 Firm-specific variables

To control how and why the sectoral stocks have changed during the COVID-19 event, it is required to first understand the basic theory of share price changes. Firm-specific variables are one of the factors which influence share prices. A very well-known valuation method, the Discounted Cash Flow (DCF) method, will be elaborated to explain how firm-specific variables can affect the share price:

$$DCF = \frac{FCF}{wacc - g}$$

The numerator is Free Cash Flow (FCF), this is the amount of money that a company has left to spend after all costs, including taxes and investments are subtracted from the revenue (Titman & Martin, 2014). The denominator is the weighted average cost of capital (wacc) minus the growth (g) of the company, where the wacc consist of the cost of debt (amount of debt times the price of debt) plus the cost of equity (price per share times shares outstanding) (Titman & Martin, 2014). So, according to the efficient market hypothesis, the share prices should reflect all information, and thus change when either the nominator or the denominator of the DCF analysis changes. To provide some examples, when a company has an increased FCF because the profitability increases and investments remain equal, and at the same time, the denominator remains equal as well, then the share price should increase according to the efficient market hypothesis. Contrary, when the cost of debt increases because the amount of debt has increased, and the FCF remains equal, then according to the efficient market hypothesis, the share price should decrease (Titman & Martin, 2014).

To control for these firm-specific variables, different book values and ratios related to FCF, debt and equity can be researched. For instance, profit margin, earnings per share, D/E ratio, ROE and market-to-book value. Then it can be identified whether entire sectors experience changes in these variable, which also significantly differ from other sectors. For instance, if an entire sector suffers from a significant decrease in FCF, and therefore experiences abnormal returns during the COVID-19 event.

To conclude, understanding and testing the firm-specific variables is desirable to understand the indirect effect of COVID-19 and whether the efficient market hypothesis is applicable.

3.1.2 Macroeconomic variables

Besides firm-specific variables, there are macroeconomic variables that influence share prices as well. Examples of common macroeconomic variables are de Gross Domestic Product (GDP) and inflation (Al-Tamimi, Alwan, & Rahman, 2011). However, since this research focusses on one country only, it is less relevant to control for these macroeconomic variables because most companies equally suffer from the changes in GDP and inflation. The only external variable which will be focussed on during this research, is the exogenous event COVID-19, which will be further discussed in section 3.3. But first, in the next section, past exogenous events will be analysed.

3.2 Exogenous events affecting the stock market

Over time, many exogenous events have affected the stock market. Exogenous events are explained as events that are out of control by the company but do affect the performance[11]. Examples of exogenous events are the global financial crisis, the dot-com bubble and for instance pandemics like COVID-19. First, examples of economic, social and political events will be discussed, their impact on the stock market will be outlined and these impacts will be related to the theories discussed in chapter two. After that, natural disasters, and specifically pandemics are covered similarly. Finally, the post-event impact will be discussed, and what long-term effects the exogenous event possibly has.

3.2.1 Economic, social and political events

First, the economic exogenous events will be discussed. Examples of economic exogenous events are the Global Financial Crisis of 2008/2009 (GFC) and the Great Depression (1929-1933). The U.S. stock market during the GFC experienced an enormous decrease, whereas the volatility increased significantly, especially in the financial sector (Schwert, 2011). This is an example of an exogenous shock with a high impact, but how did investors react during this crisis? Verheyden, de Moor and van den Bossche (2015) researched among other regions, the efficiency of the market, prior, during and after the GFC in the U.S.. The results indicate that the market is efficient prior and five years after the global financial crisis, but lost this efficiency during the GFC (Verheyden et al., 2015). This could indicate that investors have acted irrational during the GFC and thus this rejects the efficient market hypothesis and the random walk hypothesis, and confirms the behavioural finance theory. Moreover, the GFC can be perceived as a black swan event since most experienced the crisis as something highly unlikely, it had extreme impact and later it actually seemed unavoidable, the three characteristics described by Taleb (2007). So, the GFC is an example of an economic exogenous event and seems to be a black swan event with reactions according to the behavioural finance theory.

[11]UNESCWA (n.d.) https://archive.unescwa.org/exogenous-shocks

Second, the social/ political events will be outlined. The social/ political events range from elections, the Brexit, climate regulations, to terrorist attacks. Terrorist attacks for example, do negatively affect the global stock markets, especially in the first phase after the event (Nikkinen, Omran, Sahlström, & Äijö, 2008). So, terrorist attacks are exogenous shocks and have an impact, but can they be defined black swan events as well? At least the September 11 attacks are defined a black swan event (Taleb, 2007). It depends on the impact of the attack and the predictability if other terrorist attacks are considered black swan events as well (Taleb, 2007). However, there has not been another terrorist attack that resulted in the same significant impact and increased volatility as the September 11 attacks (Brounrn & Derwall, 2010). Besides being a black swan event, terrorist attacks appear to have a negative impact on the investor sentiment as well. Nikkinen and Vähämaa (2010) used option prices, which represent investors' expectation of future share prices, to create a probability density and analyse the difference between the expected options and the actual returns after the attacks. The results indicate that for all three attacks investigated: the Septembers 11 attacks, the Madrid train bomb and the London bombings, a negative investor sentiment created negative returns on the London FTSE100 index (Nikkinen & Vähämaa, 2010). So, in accordance with the behavioural finance theory.

So, terrorist attacks are examples of social/political exogenous events. Whether terrorist attacks can be perceived as black swan events depends on the size and severity of the attack. Additionally, investors appear to behave according to the behaviour finance theory. Even though that terrorist attacks have a negative impact on the stock market, natural disasters harm the stock market more (Tavor & Teitler-Regev, 2019). Therefore, the natural disasters will be discussed in the following section.

3.2.2 Natural disasters and pandemics

Examples of natural disasters are earthquakes, volcano eruptions, and typhoons. A pandemic can also be perceived as a natural disaster, however, since it has different characteristics, it is mentioned separately. Examples of pandemics are the Spanish flu, SARS, EBOLA, and of course COVID-19.

Natural disasters do strongly impact the economy and influence the stock market, however, the impact is only for a limited period of time. According to Tavor and Teitler-Regev (2019), the average decrease of the stock market after a natural disaster lasts for three days. Moreover, natural disasters may also have different impacts on different sectors. A study based on Chilean natural disasters found that retail, construction and banking were positively affected, whereas real estate, food, steel and forestry were negatively affected (Ruiz & Barrero, 2014). This could be explained by the destructions and needs of the particular disasters. For instance, construction probably increased since there was a need to rebuild buildings and banking increased because there was a higher demand for credit (Ruiz & Barrero, 2014). This would indicate that there is an efficient market during these events, since the available information is immediately reflected in the share prices. Moreover, most natural disaster cannot be classified as black swan events since most natural disasters are predictable or calculable (Taleb, 2007).

Then pandemics, pandemics have been intensely researched as well. For instance, Ichev and Marinč (2018) find that the Ebola outbreak resulted in negative stock returns in the concerning areas and that the impact is most forceful when there is excessive media coverage. Thus, investors are sensitive to the media influence, this could be the tone, the fear, or the extent of media coverage. This could indicate that during the Ebola outbreak, investors acted irrational, which confirms the behavioural finance theory.

Another example of a pandemic is SARS. A study researching several Asian countries and Canada during SARS, shows that except for China and Vietnam, all other stock markets have not experienced a significant negative return (Nippani & Washer, 2004). Nevertheless, studies focussing on the sectoral return, present more sectoral specific results. Chen, Jang, and Kim (2007) concluded that the tourism industry was hit the hardest in the Taiwanese stock market. This was measured based on the day of the SARS outbreak and the day after, so short term. Similarly, Chen, Cheng, Tang and Huang (2009) found that the hospitality industry had the most negative returns during the SARS outbreak and that the biotech firms created the most positive returns. Contrary to the EBOLA pandemic, SARS would lean more towards the efficient market hypothesis, since the sectors which are financially impacted, also have increased or decreased stock returns, whereas the sectors which have no or limited financial impact, have normal stock returns.

To summarize, most natural disasters only lead to a short term impact on the stock market. For pandemics, the impact on the stock market differs. Whereas during EBOLA, the stock market experienced negative returns, and the behavioural finance theory seems to apply, during SARS only certain sectors experienced negative returns, here the efficient market theory seems more suitable. Since now, only the short term effects of exogenous events on the stock market have been discussed, next, the post-event effects of exogenous events will briefly be highlighted.

3.2.3 Post-event impacts

Since the stock market not only experience short term impacts from exogenous events, but possibly also experience long term effects, it is relevant to briefly discuss the aftermath impact of exogenous events. Verheyden et al. (2015) discovered that only five years after the GFC, the U.S. stock market returned to its efficient equilibrium. So, this indicates that because of the GFC, the stock market not only experienced a short term impact, but a long term impact as well. Similarly, the September 11 attacks, seem to have impacted the systematic market risk in the post-event era. (Brounrn & Derwall, 2010). Contrary to the long term effects of these exogenous events, natural disasters have on average a very short impacting period, three days and therefore no aftermath effect (Tavor & Teitler-Regev, 2019).

To conclude, it depends on the exogenous event whether the stock market experiences a long term effect.

3.3 COVID-19 affecting the stock market

Finally, existing literature regarding the effect of COVID-19 on the stock market will be discussed. The previous section contained a review of the effect of former exogenous events on the stock market, including past pandemics. Since COVID-19 is a pandemic, it is most suitable to compare this pandemic to previous ones. David, Inácio Jr. and Tenreiro Machado (2021) for instance, already compared the impact of different pandemics (EBOLA, MERS, and SARS) to COVID-19. Accordingly, all pandemics had an impact on the global stock market, however, except for COVID-19, all other pandemics had a swift recovery. Besides that, COVID-19 impacted the share prices with a higher volatility, thus increased risk (David et al., 2021). So, the stock market seems to be impacted stronger by COVID-19 compared to other pandemics. Baker et al. (2020) confirmed this result: "*No previous infectious disease outbreak, including the Spanish Flu, has affected the stock market as forcefully as the COVID-19 pandemic."* This difference can presumably be explained by the unique governmental restrictions implemented during COVID-19, and the amount of media coverage, which both are not comparable to previous pandemics. (Baker et al., 2020). So, COVID-19 seems to have an even more forceful effect on the stock market than past pandemics, and since pandemics are a recurring phenomenon, it is meaningful to analyse its impact and possibly learn for the future.

3.3.1 COVID-19 and volatility

This increased risk, or volatility, has been recognized by individual studies on COVID-19 as well. Ali, Alam, and Rizvi (2020) found that the volatility on the global stock markets increased since the pandemic has been declared by the World Health Organisation on March 11, 2020[12]. Similarly, Zhang, Hu, and Ji (2020) noticed an increase in investor uncertainty on the global financial market since the pandemic was declared, which in turn increased the volatility. Besides that, a correlation was discovered between the number of infected and diseased in a country caused by COVID-19, and the national stock market reactions (Zhang et al., 2020). So, the more

[12] WHO (2020). Coronavirus Disease (COVID-2019) Situation Reports. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/

serious the outbreak in a country, the more severe the stock market reaction within that country, and the higher the risk. This would indicate that the stock market reaction differs across countries.

3.3.2 COVID-19 across countries

This difference between countries has been researched as well. Ashraf (2020) identified a pattern between the number of COVID-19 cases confirmed and the decrease in the global stock market between January 22, 2020 and April 17, 2020 for 64 countries. So, when the number of confirmed COVID-19 cases increased in a country, the share prices correspondingly decreased. This correlation was strongest in the first period after the first confirmed case within the country and was recognized in all 64 countries (Ashraf, 2020). Whereas Ashraf (2020) found a negative significant correlation between the number of COVID-19 cases and share prices across all countries, Ngwakwe (2020) observed a significant difference between the stock index changes between the United States and China. The Dow Jones index value significantly decreased, whereas the Chinese Stock Index significantly increased when comparing the 50 days before the pandemic, with the 50 days during the pandemic. So, there appears to be a difference in the reaction of the stock markets during COVID-19 across these countries. This difference between countries may possibly be caused by the different life and work restrictions across countries. For instance the length of the lockdown, curfew and other restrictions. Likewise, Ali et al. (2020) claim that the Chinese stock market recovered significantly faster than the US stock market because of the restrictions implemented by the government. Even though the restrictions in China have positively influenced the stock market returns, policy restrictions may also create even more uncertainty and long term complications according to Zhang et al. (2020).

Another possible explanation for the difference in stock return between China and the U.S. could be linked to the behavioural finance theory discussed in section 2.3. Investors could have reacted irrationally because of fear (Brealey et al., 2020) . Salisu and Akanni (2020) have studied the amount of fear across several countries from March 11 until April 30, 2020. The results indicate that the US, the UK and Russia have the highest average Global Fear Index (GFI), 77.37, 77.22, and 87.50

respectively, whereas China (31.85) and Iran (56.98) appear to have the lowest amount of fear among citizens. So, according to Salisu and Akanni (2020), there is a substantial difference in the amount of fear between the US and China, which could also explain the difference in abnormal stock returns between these countries. Moreover, Italy and Germany also perceived a relative high fear index, 60.54 and 70.87 respectively (Salisu & Akanni, 2020). The question however, is, do these countries experience high abnormal stock returns as well. Shehzad, Xiaoxing, and Kazouz (2020) compared the impact of COVID-19 of stock indices in Japan, China, the US, Germany and Italy. Identified was that all five countries experienced negative returns during COVID-19, however, the US, Italy and Germany were more forcefully impacted than China and Japan. Notifiable, is that a difference in impact was identified between the stock indices within the US as well. Namely, the S&P500 index appeared to be impacted more forcefully than the NASDAQ Composite Index (Shehzad et al., 2020). This indicates that there is indeed a desire to study the differences in sectoral returns during COVID-19.

3.3.3 COVID-19 and the effect on sectors

Besides country-specific differences, the governmental policies will likely be reflected in the overall stock returns across different sectors as well. For instance, a travelling restriction will presumably negatively influence the profits of the travel industry, whereas a lockdown likely will positively influence the revenues of the gaming industry. This sectoral difference is researched by He, Sun, Zhang and Li (2020) within China. The results present that not all sectors are equally impacted. Manufacturing, for instance, was positively influenced by COVID-19 in China. This could have impacted the faster recovery time of China as well, since manufacturing accounts for 27.2% of the GDP, whereas it only accounts for 11.2% of the GDP in the United States[13]. Additionally, Al-Awadhi, Alsaifi, Al-Adwadhi, and Alhammadi (2020) found that in the first phase of COVID-19 (January 10th – March 16th 2020), the sectors information technology and medicine manufacturing, experienced a positive significant stock

[13] Statista (2020). The Global Decline of Manufacturing. https://www.statista.com/chart/20148/manufacturing-value-added-as-percent-of-gdp-in-major-economies/

return, whereas the sectors beverages and air, water, and highway transportation, experienced a negative significant stock return. These findings were based on the Shanghai Stock Exchange. Similar results were provided by Panyagometh (2020), who also highlights that pharmaceutical companies (both products and services), experienced positive results on the Thai stock market and that transportation/ logistics and food and beverage sectors experienced negative results. In addition to that, the banking sector, finance and securities, and energy and utilities experienced negative stock results as well (Panyagometh, 2020). Moreover, in the United Kingdom, similar results were discovered. Tourism, including the airline industry, banking, and insurance experienced negative results, whereas the medical sector and biotech research experienced positive results (Griffith, Levell, & Strout, 2020). Remarkably, however, is that Griffith, et al. (2020) did not find negative, but instead, positive results in food manufacturing, and negative results in the large manufacturing industries in the United Kingdom. This may be caused by the different regulations between China, Thailand and the United Kingdom, but may possibly also be caused by the different mappings of the sectors.

So, based on current literature, COVID-19 had a significant effect on the stock market. Although most sectors in different countries appear to have similar results, there are some discrepancies. So, it is relevant to conduct research regarding the effect of COVID-19 on the different sectors in the US stock markets. Moreover, since most research is conducted based on the first phase of COVID-19, research on both the short and long term effects of COVID-19 on the US stock market sectors will contribute to the current literature.

3.4 Hypotheses

In this final section of chapter 3, two hypothesis will be created based on both the theoretical framework from chapter two, and the existing literature discussed in chapter three.

Based on the current literature, I expect that the share prices of the overall US stock market will decrease as of the discovery of the first COVID-19 patient in the US. Additionally, based on the market trend, I expect that the negative abnormal stock returns will stop when the federal reserve has pledged to support the economy. This would confirm the behavioural finance theory, since it would provide the investor with trust.

Hypothesis 1: "*Between January 21, 2020 (the first COVID-19 patient in the US) and March 23, 2020 (pledge of the federal reserve to support the economy), the average of all sectors on the US stock market, will experience a significant abnormal decrease in the stock returns.*"

This can be measured by implementing several event dates within this period and analysing whether the abnormal returns of these US sector have experienced significantly negative returns.

Second, based on the literature discussed on the effect of COVID-19 on the different sectors across countries in section 3.3, I created a table to summarize the sectors which were impacted the most (table 1). By applying these sectors on the mapping of the BvD sectors that I will use during the research (Appendix A, table 1), I expect that the sectors of Manufacturing, the Public Administration, Education and Health Social Services and the Biotechnology and Life Sciences will perceive positive abnormal returns during the COVID-19 event, whereas the sectors Banking, Insurance, & Financial Services, Transport, Freight & Storage, the Travel, Personal & Leisure and Utilities experience negative abnormal returns during the COVID-19 events.

Hypothesis 2a: The sectors of Manufacturing, the Public Administration, Education and Health Social Services and the Biotechnology and Life Sciences will perceive positive abnormal returns during the first three events of COVID-19

Hypothesis 2b: The sectors Banking, Insurance, & Financial Services, Transport, Freight & Storage, Travel, Personal & Leisure and Utilities experience negative abnormal returns during *the first three events of COVID-19*

Table 1

Summary of the sectors that are impacted during COVID-19

Author(s)	Event	Country	Positively impacted	Negatively impacted
He, Sun, Zhang and Li (2020)	COVID-19	China	- Manufacturing	
Al-Awadhi, Alsaifi, Al-Adwadhi, and Alhammadi (2020)	COVID-19	China	- Information technology - Medicine manufacturing	-Beverages - Air, water, & highway transportation
Panyagometh (2020)	COVID-19	Thailand	-Pharmaceutical	-Transportation & logistics - Food & beverage - Banking sector - Finance & securities - Energy & utilities
(Griffith, Levell, & Strout, 2020).	COVID-19	UK	-Medical sector - Biotech -Food manufacturing	- Tourism & Airline - Banking & insurance - Large manufacturing

4. Research Method

4.1 Prior Research

Most studies on the effect of COVID-19 apply an event study to measure abnormal returns. Table 2 provides a brief overview of methods that have been implemented. The study of Goodell and Huynh (2020) for instance, aims on finding the effect of COVID-19 on the different sectors on the stock market in the United States. They apply the market model event study to measure the cumulative abnormal returns by comparing the actual returns with the expected returns (Goodell & Huynh, 2020). This type of event study also has been implemented by He et al. (2020), who also research the effect of COVID-19 on the different sectors in China. Additionally, two other studies which researched the effect of SARS on the different sectors in Taiwan, applied the market model event study as well (C.-D. Chen et al., 2009; M.-H. Chen et al., 2007). Since these are all studies which research the effect of a pandemic on the different sectors in the stock market, it seems a logical choice to apply this method within this study as well.

Table 2

Overview of authors and their methodology implemented

Author	Methodology
Goodell and Huynh (2020)	Market model event study
He et al. (2020)	Market model event study
C.-D. Chen et al., 2009).	Market model event study
M.-H. Chen et al., 2007	Market model event study
Ashraf (2020)	OLS Regression
Al-Awadhi et al. (2020)	OLS Regression

Nonetheless, there are studies regarding the effect of COVID-19 on the stock market who use a regression analysis. Ashraf (2020) for instance, studied the correlation between the amount of confirmed cases and deaths to the stock market return. The advantage of a regression, is the ability to control for third variables. Similarly, Al-

Awadhi et al. (2020) also applied a regression with the amount of deceased and deaths as independent variable. Moreover, they claim that COVID-19 has no clear event date, which makes it harder to implement an event study and therefore applied a regression (Al-Awadhi et al., 2020). This could however, be diminished by implementing multiple event dates and event windows. Nevertheless, regression would reduce bias and multicollinearity (Al-Awadhi et al., 2020; Ashraf, 2020).

So, both the event study and the regression have been applied within prior research. For the purpose of this research, the main method that will be applied is the event study, since most studies that also studied sectoral returns have implemented the same method with success. However, since a regression model can test whether other variables have influenced the results, a regression will implemented to all the sectors which have experienced abnormal returns, to control for other explanatory variables.

4.2 Event study

Event studies attempt to verify if a certain event had a significant impact on the stock returns (Benninga, 2014). To achieve this, the expected returns (returns under normal circumstances) are subtracted from the actual returns, which result in the abnormal returns. So how much do the actual returns deviate from the expected returns. For this study, the US stock market will be researched. To calculate the abnormal returns, and event date and window have to determined. This will be discussed next.

4.2.1 Event dates and windows

To apply the market model event study, the event dates had to be determined. Since Al-Awadhi et al. (2020) argues, that COVID-19 has not one, clear event date, it is decided to apply four event dates within this study. Then, the event dates abnormal returns of the different event dates can be compared, this will increase reliability because there is a lower chance on missing important event dates. There are four event dates that are relevant to the US stock market and interesting to investigate (table 3).

Table 3

Overview of the event dates

Event nr.	Event date	Event description
Event 1	January 21, 2020	First COVID-19 patient was discovered in the US[14]
Event 2	February 3, 2020	US declares a public health emergency[15]
Event 3	March 11, 2020	WHO declares COVID-19 a pandemic[16]
Event 4	March 23, 2020	Federal Reserve pledges to support the economy[17]

First, January 21, 2020, when the first COVID-19 patient was discovered in the US. This indicated that COVID-19 now not only was a problem in China, but became a domestic problem as well. Second, the date when the US declares a public health emergency, on February 3, 2020. Similarly, this indicated that the US government recognize that the COVID-19 virus is a serious problem. Third, when the WHO declares COVID-19 a pandemic, on March 3, 2020. Now the virus has been recognized as a globally health problem. Finally, the day that the Federal Reserve pledged to support the economy, on March 23, 2020. The final event date is different from the other three. Where the other three events represent the recognition of problems related to the COVID-19 virus, which could lead to fear, the fourth event date represents progress, which could lead to trust. By comparing these four events, it can be determined which event date has had the most impact on the sectors in the US stock market in the short term, and whether new information immediately is reflected in the share prices, according to the efficient market hypothesis, or whether the behavioural finance theory is more applicable.

To control in what time span the market responses, first the abnormal returns on the event date [0,0] will be described. After that, according to Benninga (2014), the three most common event windows are [-3,3], [-5,5] and [-10,10]. These three different event windows are applied for all for event dates to take pre-event leakage and delay in response time into consideration. Figure 2 provides a conceptual model of the event

[14] AJMC (January 1, 2021) A timeline of COVID-19 Developments in 2020 Retrieved from: https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020

[15] AJMC (January 1, 2021) A timeline of COVID-19 Developments in 2020. Retrieved from: https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020

[16] WHO (April 27, 2020). WHO timeline – COVID-19. Retrieved from: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19

[17] Federal Reserve (March 23, 2020) Federal Reserve announces extensive new measures to support the economy. Retrieved from: https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm

data. The figure in the middle represents the event window, where 0 represents the event windows from table 3, and $((T_2 - T_3)$ represent the event windows [-3,3], [-5,5], and [-10,10]. Testing for different event windows can help control for how quick the market responded to public information during COVID-19, which helps to assess the efficient market hypothesis.

Besides the event window, an estimation window is necessary to calculated the expected returns. The estimation window is determined according to Benninga (2014), who claims that the most common estimation window $(T_0 - T_1)$ is taking 252 trading days before the event date. Additionally, an estimation window of 252 trading days would assure robustness (Benninga, 2014)**.** Since the sample size remains large enough when using the estimation window of 252 trading days, this is applied to ensures robustness. Nevertheless, for the ease of the calculations, the same estimation window has been applied to all event dates. The estimation window was established from January 3, 2019 until January 3, 2020 (252 trading days). This means that T_0 = January 3, 2019 and $T_1 =$ January 3, 2020 (figure 2).

Additionally, since there is limited research available regarding the long term impact of COVID-19 on the stock market, a post-event window is added to determine this long term impact. The post event window will start on the day of the event window $(T_4 - T_5)$ and will consist of 13 different event windows: [0,20] [0,40] [0,60] [0,80] [0,100] [0,120] [0,140] [0,160] [0,180] [0,200] [0,220] [0,240] [0,260]. According to Benninga (2014), a post-event window can last between a month and multiple years. Since there is no previous research available on the long term effect of COVID-19 on the stock market, it was deliberately chosen to study the post event window in steps, until the last day available during the research. So you can see whether there is a long term effect, and if yes, for how long it lasts.

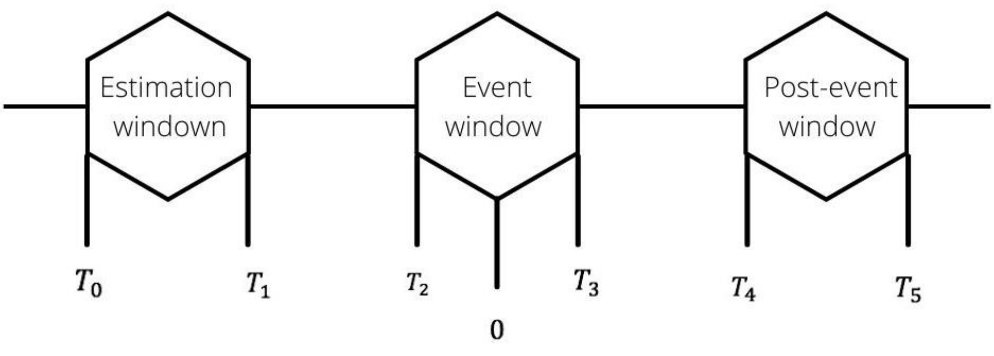

Figure 2: Conceptual model of event data

To provide better understanding of how figure 2 is implemented, an example will be provided based on event date March 11, 2020, and the event window of [-3, 3]. In this example the event window (($T_2 - T_3$) is March 6, 2020 until March 16, 2020. The estimation window ($T_0 - T_1$) will be January 3 , 2019 until January 3, 2020 and the post event window of [0,260] (($T_4 - T_5$) will be from March 12, 2020 until March 24, 2021.

4.2.1 Event study models

There are different models that can be implemented within an event study to calculate the abnormal returns. First, the different models will be briefly discussed, then, based on the literature, one model will be applied within this study, the market model. There are three main models within an event study which estimate the abnormal returns: the mean adjusted model, market adjusted model and risk adjusted models.

First, the most simplistic model is the mean adjusted return, which calculates the abnormal return by subtracting the average return from the estimation window, from the actual return (Brown & Warner, 1985).

Second, the market adjusted model. The market adjusted model also uses the actual returns, but instead of subtracting the expected returns of the individual stock from the actual returns, the actual returns of the market index are subtracted from the actual returns of the individual stock (Benninga, 2014). So, for this method, the individual returns of a stock are compared to the market index, and how much it deviates from the market index.

Finally, the risk adjusted model, which actually consists of three separate models: the market model, the multi-factor model and the Capital Asset Pricing Model (CAPM). First, the market model is the model which has mainly been implemented in similar research studies discussed in section 4.1. Moreover, the market model is more specific than the previous two discussed, the expected returns are namely calculated with help of an ordinary least square (OLS) regression and the market index (Benninga, 2014). Second, within the multi-factor model, not only the market returns are used to calculate the abnormal returns, but the industry returns are used to explain the industry-specific variation as well (Benninga, 2014). Lastly, CAPM, the formula of CAPM is similar to the market model. Nevertheless, to calculate the CAPM model you will need the beta of each individual stock, as well as the risk-free rate, which both are difficult to obtain (Brealey et al., 2020). CAPM appears to be a more theoretical model, rather than a simple implementable one.

To summarize, for the purpose of this research, the market model will be implemented. First, the mean adjusted return model and market adjusted return model do fulfil the purpose of calculating abnormal returns, however, these methods are relatively simplified. Therefore the market model implies to be more powerful. Additionally, similar papers, discussed in 4.1, have applied this model before, and based on the conclusion of Brown and Warner (1985), that the market model provides very specific results under most circumstances. The CAPM model would have similar outcomes however, this is a theoretical model, whereas the market model has more practical implications. Finally, the multi-factor model implements industrial factors to more precisely calculate the abnormal returns. However, since the purpose of the research is to calculate the sectoral abnormal returns, rather than individual stock returns, this would hav no additional value. In the following section, the market model will be precisely elaborated.

4.2.2 Market model

The market model will be implemented for this research. It is the most commonly used model in the event studies and the most specific method since the expected returns are calculated with help of an ordinary least square (OLS) regression (Benninga, 2014). An event study exists of the event window, which is the day of the event with a length of normally 3, 5 or 10 days, and the estimation window, which usually exists of 252 trading days (Benninga, 2014). Besides this, a post-event window is not common but can be implemented as well. This enables the assessment of the long-term effects of an event (Benninga, 2014). This will be implemented within this research, since the longer-term effects of COVID-19 on the stock market in the US have not been researched yet, and this will provide a more fully overview of the impact of COVID-19 on the US stock market.

The implementation of the market model consists of several steps. First, the daily US share prices of the individual stocks have been transposed into actual returns. For this the following formula has been applied:

$$\boldsymbol{r_{it} = \frac{closing\ price_t - closing\ price_{t-1}}{closing\ price_{t-1}}}$$

So, the actual returns have been calculated by taking the closing price on day t, minus the closing price of day t-1, so the closing price of the day before day t. Then this was divided by the closing price t-1. This is applied to all companies, for all days from the estimation window until the post-event window. Now the actual returns show whether each individual firm has experienced an increase or decrease in share price compared to the trading day before, and by what percentage the share price has changed.

After this, the expected returns were calculated. Within the market model, the market index together with the estimation window are employed to calculate the expected returns. For the purpose of this research, the largest market index of the US was implemented, the S&P 500. First, the returns of the market index were calculated similarly as described above. Then, for each individual stock, the sensitivity towards the market index was calculated based on the estimation window. This has been executed by calculating the alpha and beta, or in other words, with the intercept and slope. The intercept and slope have been calculated with a OLS regression. So first, for each individual firm, the alpha (α_i) and the beta (β_i) have been calculated during the estimation period (so before the event , by regressing the effect of the S&P500 (independent variable), on the individual firms (dependent variable). Then, when the alpha and beta are known for each individual firm, the expected return can be calculated with the following formula:

$$\boldsymbol{E(r)_{it} = \alpha_i + \beta_i r_{Mt}}$$

So, the beta (β_i) of the individual firm was multiplied by the actual returns of the S&P500 market index (r_{Mt}) and adding the alpha (α_i). Now, the daily expected return of each individual firm has been calculated.

After this, the Abnormal Returns (AR) of the individual stocks can be calculated. The AR is actually the difference between the actual return (r_{it}) and the expected return ($E(r)_{it}$):

$$\boldsymbol{AR_{it} = r_{it} - E(r)_{it}}$$

For example, when the abnormal return is 0.01, then the actual return is 1% higher than the expected return. This is has been calculated for all individual stocks.

Then, the Cumulative Abnormal Returns were calculated for all. The CARs is the are the abnormal returns within the event window cumulated. So for instance, the CAR of March 11, 2020 [-3,3] are the ARs of the three trading days before March 11, 2020, the event date itself and the three trading days after March 11, 2020 cumulated. This has been executed for all four events, with their accompanying event windows. The following formula was applied:

$$\boldsymbol{CAR_{(t_1,t_2)} = \sum_{i=t_1}^{t_2} AR_{i,t}}$$

After all the CARs for all event dates and windows for all companies have been calculated, the sectoral means and the statistical tests have been executed with the statistics software program SPSS. The data that had been retrieved from Orbis, already connected the companies to one of the 28 BvD sectors. So, for each sector, the mean of the companies belonging to that sector have been calculated in SPSS. Then the significance has been tested with a one sample t-test. The following formula is applicable for the one sample t-test:

$$\boldsymbol{t} = \frac{(\bar{\boldsymbol{y}} - \boldsymbol{\mu})}{\boldsymbol{s}/\sqrt{\boldsymbol{n}}}$$

When a company has a normal return, then the expected return equals the actual return, thus a normal return is zero. This normal return (μ) is subtracted from the abnormal return ($\bar{y}$). This outcome ($\bar{y} - \mu$) is divided by the standard error (s) divided by the square root of the sample size ($\sqrt{n}$). When the t-test statistic is significant, then the abnormal return is significantly different from 0.

To conclude, these are the theoretical steps that have been executed to conduct the market model. After the CARs had been calculated for each event date and window for each of the sectors, a student's t-test was performed in SPSS to calculate whether each sector experienced significant abnormal returns, so whether the actual returns significantly differed from the expected returns. All the data that was employed to perform these steps will be further elaborated in chapter 5.

4.3 Post-event analysis

Besides the market model event analysis, a post-event analysis has been executed as well. The post-event analysis has been added to the paper since most studies on COVID-19 have not researched the long-term effect until now. Moreover, as discussed in section 3.2.3, there are exogenous events that have experienced long term effects, for example, the Global Financial Crisis and the September 11 attacks. Even though most exogenous events do not suffer from a long term impact, it is relevant to investigate whether COVID-19 belongs to the exogenous events with a long term impact or not. The post-event impact will be measured with the same calculation as the market model, only now the event windows will cover the periods after the event date. Since this is only a small part of the research, only the post-event analysis will be performed from one event day, the event day with the most significant abnormal returns: March 11. The following event windows have been tested: [0,20] [0,40] [0,60] [0,80] [0,100] [0,120] [0,140] [0,160] [0,180] [0,200] [0,220] [0,240].

4.4 Regression analysis

Besides the event studies, additionally, a regression analysis has been performed to test whether third variables can explain the CARs. This has been implemented to increase the study's robustness and test for other explanatory, firm-specific variables, discussed in section 3.1.1. Several other studies have implemented a regression analysis to control for variables. For instance, Xiong et al. (2020) conducted a regression analysis to control for firm-specific variables within an event study of the effect of COVID-19 on the stock market in China. The following multiple regression equation was be implemented based on a combination variables used in existing literature, and the available firm-specific information retrieved from Orbis (the data base from which all the firm-specific information has been retrieved).

$$CAR_{i,t}[-\tau, +\tau] = \alpha_0 + \beta_1 SIZE_{i,t} + \beta_2 LEV_{i,t} + \beta_3 ROE_{i,t} + \beta_3 MTB_{i,t} + \varepsilon_{i,t}$$

The dependent variable in this regression will be the CAR of the individual companies. The CAR within this regression, will be based on event date 3: March 11, 2020, similarly as the post-event analysis. This event date was deliberately chosen since the most, and the highest significant abnormal returns occurred around this event date. All the three event windows will be implemented: [-3,3], [-5,5], and [-10,10]. Table 4 provides an overview of the variables applied in the regression analysis, accompanied with their definitions and the source from which the variables are retrieved.

Based on the available firm-specific information of 2020in the Orbis data base, small changes in the variables had to be made compared to the variables retrieved from the sources. First, the SIZE variable was defined in Xiong et al. (2020) as the total assets of a company. However, since there was no available information on the total assets in Orbis, the number of employees was applied in this research to define the SIZE variable. Second, to indicate the financial performance, Xiong et al. (2020) applied the variable Return on Assets. Similarly, since this information was not available within the sources used during this research, the variable Return on Equity was applied instead, to indicate the financial performance.

Table 4

Variable definitions of regression

Type of variable	Variable	Definition	Source
Dependent variable	CAR [-т,+ т]	Cumulative abnormal returns of the event date March 11, 2020, and the three event windows: [-3,3], [-5,5], [-10,10]	
Independent variables	SIZE	The size of each company is measured by the number of employees	Xiong et al. (2020)
	LEV	The leverage is measured with the debt/equity ratio	Xiong et al. (2020)
	ROE	The Return on Equity calculated as net income divided by the total equity and represents the financial performance	Xiong et al. (2020)
	MTB	The market-to-book ratio is the market value divided by the book value and also represents the financial performance	Al-Awadhi et al. (2020)

5. Data

In the following section, the data and information applied to execute the study will be discussed. First, the daily share prices are discussed, then the sectoral data will be reviewed and finally, descriptive statistics will be provided before continuing to the results chapter.

5.1 Daily share prices

For this quantitative research, secondary data was implemented. To research how COVID-19 influenced the sectors on the US stock market, first US individual stock data has to be retrieved. The sample consists of daily share prices of the two major US stock markets: NYSE and NASDAQ. These daily share prices have been gathered from January 2nd,2019 until March 24rd 2021 from EODATA. The total amount of companies from which these daily share prices is retrieved is 5663. Nevertheless, there are companies that listed after January 2nd, 2019 or stopped before March 24rd, 2021, these are the companies with missing data, and those companies are excluded, which results in a sample of 4117. Since this study is focused on the difference between sectors, it is essential that all companies are assigned to a sector, this will be elaborated on next.

5.2 Sectoral data

The sectoral data that was used during this study are the BvD sectors and are retrieved from the ORBIS data base. The reason to choose the BvD sectors was since these sectors were available to me via the Orbis data base. The BvD sectors consist of 28 different sectors. Five companies were not assigned to a sector by Orbis and these five companies have been excluded from the sample as well to prevent bias, this resulted in a final sample size of 4112. With help of the ticker symbols of the listed companies, the sectors could be connected to the daily share prices of the companies.

To compare this sample to past research, He et al. (2020) used a sample size of 2895 listed companies in China and 18 different sectors, Al-Awadhi et al. (2020) used a sample size of 1579 listed firms and 10 different sectors, whereas Goodell and

Huynh (2020) compared 49 different sectors (sample size unknown). The sample size of this research is larger and the number of sectors lies in between the studies. So, based on past research this appears to be a reasonable dataset. Moreover, since the ORBIS database is the only database that is available to me at this point, it is the most suitable data set to prevent subjectivity once the sectors have to be divided by the researcher.

5.3 Descriptive statistics S&P 500 index

First, before the results will be analysed, some descriptive statistics of the data set will be provided. Since the sectoral returns are compared to the S&P 500 index, first some descriptive statistics of the S&P 500 index will be provided. Figure 3 displays an overview of the mean closing prices of the S&P 500 index between December 2019 and April 2021, which represent the dates before and during the outbreak of the COVID-19 virus. As of February 2020, there is a decrease in the index price and by July/ August, the share prices have been increased back to the level of before February 2020. The start of 2020 also represents the period when the COVID-19 virus began to expand.

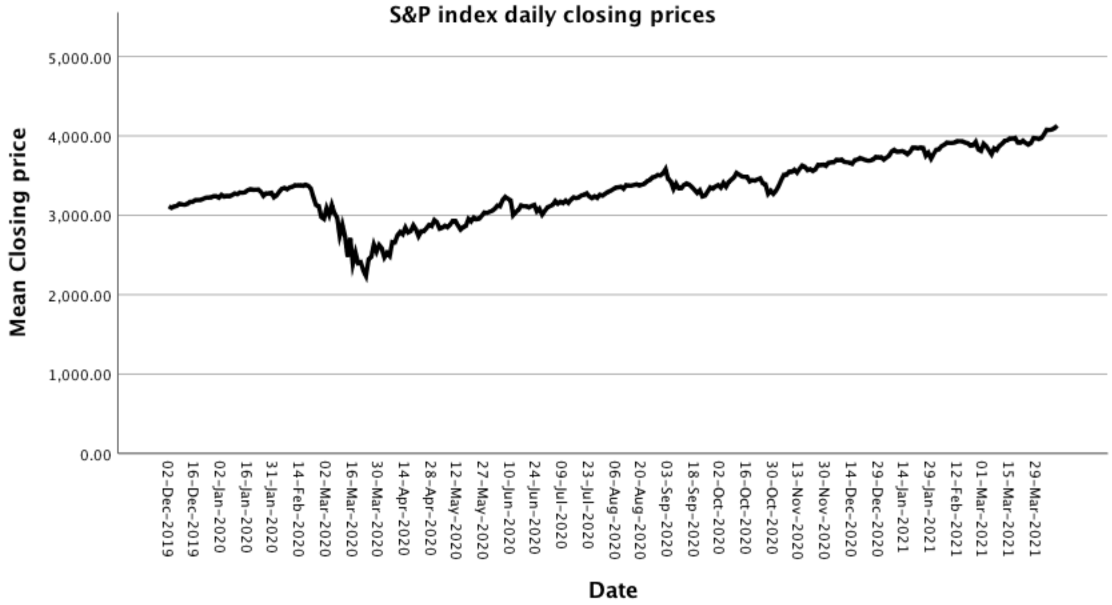

Figure: 3 Mean closing prices of the S&P 500 between December 2019 and April 2021.

Additionally, figure 4a provides the actual returns of the S&P 500 index. This shows that between February and May 2020, the returns fluctuated intensely. Figure 4b represents the standard deviation over this same period of time, this indicates that the volatility increased drastically between February 2020 and April 2020.

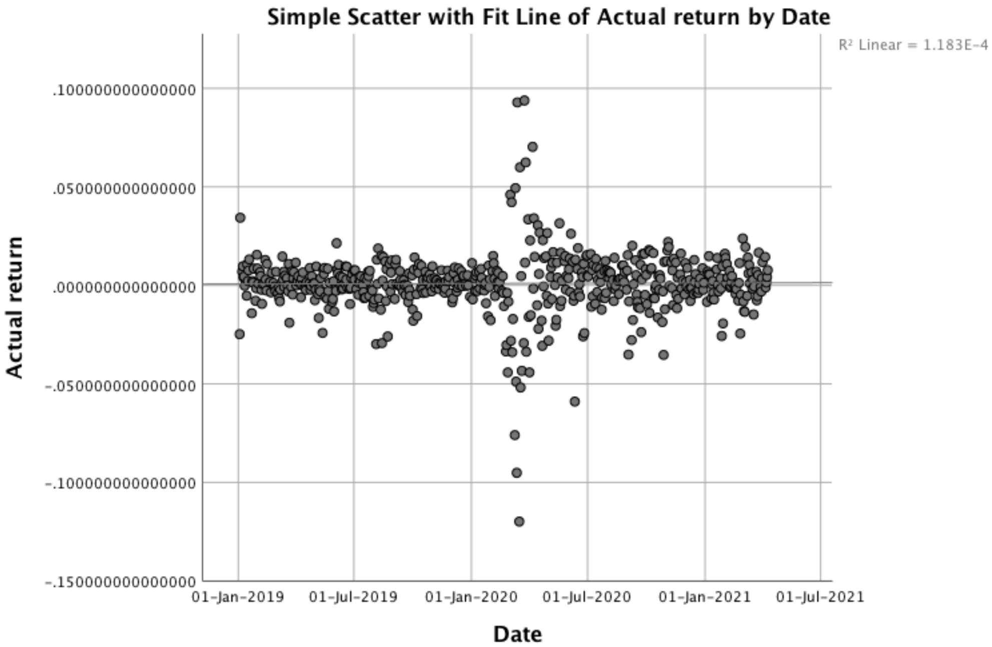

Figure 4a: actual return of the S&P 500 index between January 2019 and June 2021

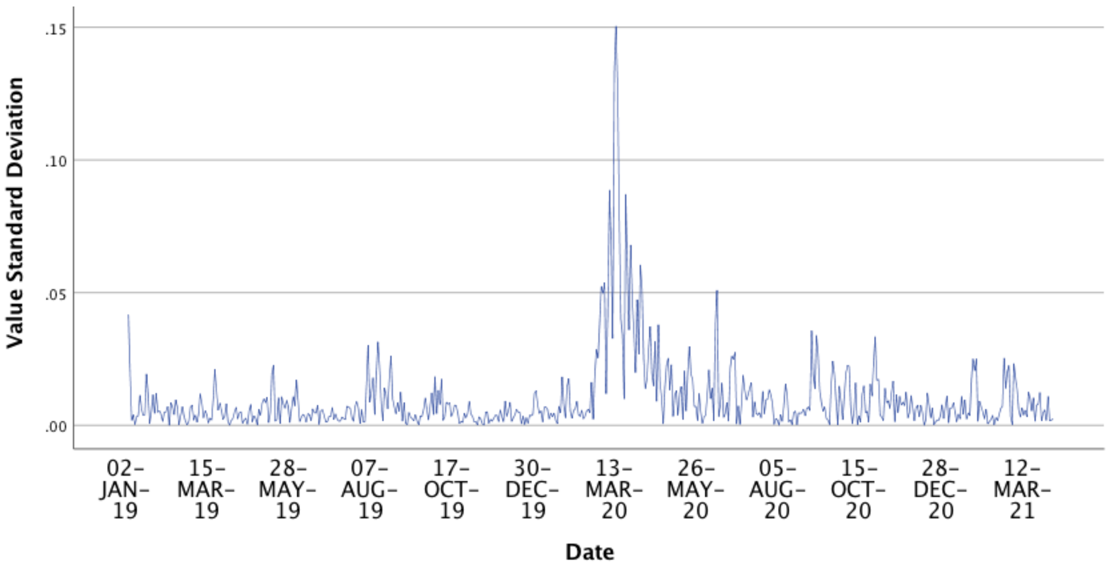

Figure 4b: the rolling volatility of the S&P 500

So, the S&P500 index experienced a significant decrease between February and April 2020 and volatility increased considerably during the same period

5.3 Descriptive statistics sectoral data

For the purpose of this research, it is relevant to discover whether specific sectors where impacted significantly more or less than expected according to the flow of the S&P 500 index. However, to enable to interpret this well, first descriptive statistics are required. Appendix A table 1 provides a frequency table of these BvD sectors.

Notably, is that not all sectors have an equal amount of companies represented within the sectors. For instance, the sector Agriculture, Horticulture & Livestock has 8 companies represented in the sector, whereas Banking, Insurance & Financial Services has 935. This difference is important to consider when analysing the results, because sectors with a lower amount of companies represented in the sector can possibly endanger the validity and reliability of the results.

Additionally, before the different event windows of the four event dates are analysed, it is important to first analyse the Abnormal Returns (ARs) on the event days for all sectors. First, to see which event day seems to be impacted the most, and second, to see how quickly the market responded to the events when compare the ARs of the event days, with the CAR of the event windows. Appendix A table 2 provides the ARs of the 28 BvD sectors for all four event days [0,0]. The AARs provide a clear overview of the average abnormal returns of all sectors combined for all four events. This means that events 1-3 have negative average abnormal returns on the event dates [0,0], event 1 (-0.27%), event 2 (-0.17%) and event 3 (-1.06%), whereas event 4 appears to have a positive average abnormal return (+0.57%). The event that seems to be impacted the most on average on the event date [0,0], is event 3, on March 11, 2020, with an average abnormal return of -1.06%. Additionally, events 3 and 4 also experienced the highest volatility, 0.0146 and 0.0232 respectively.

Moreover, figures 5a-5d provide a more visualized image of the sectoral abnormal returns on the event dates 1-4. First of all, you also see very clearly in these figures, that the majority of the sectors of events 1 and 3 experience negative abnormal returns, whereas the majority of the sectors during the fourth event

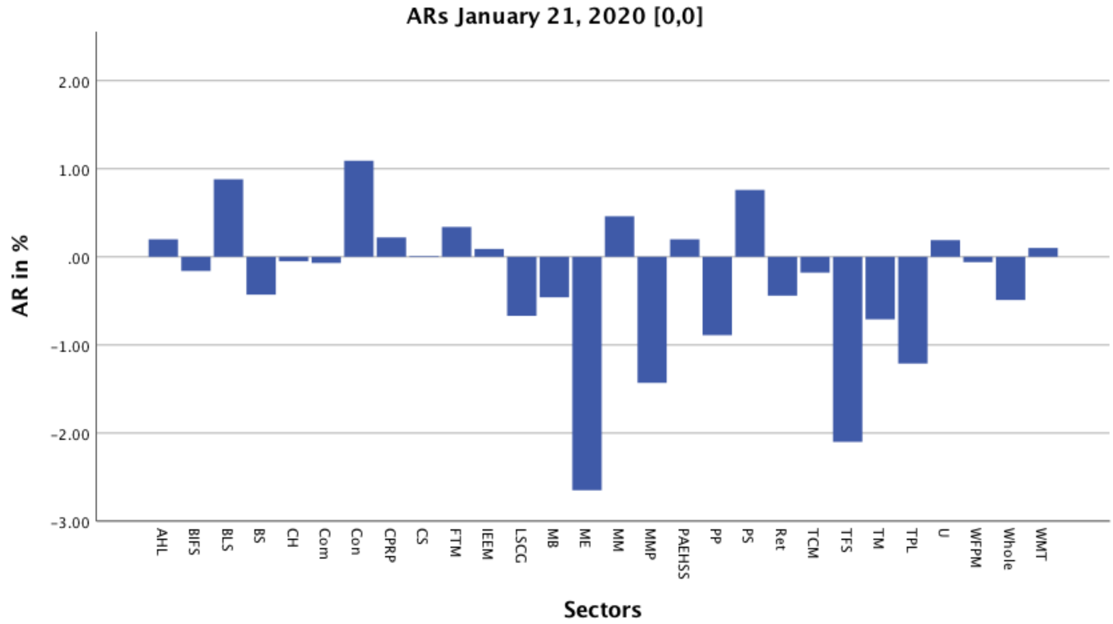

Figure 5a: The sectoral ARs on event date 1 [0,0]

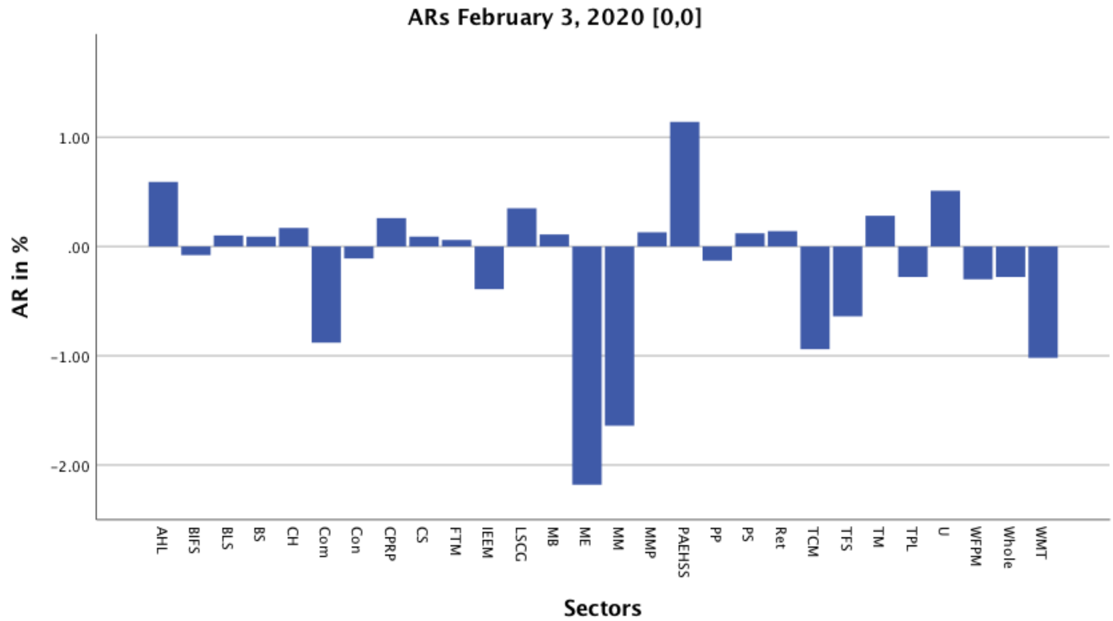

Figure 5b: The sectoral ARs on event date 2 [0,0]

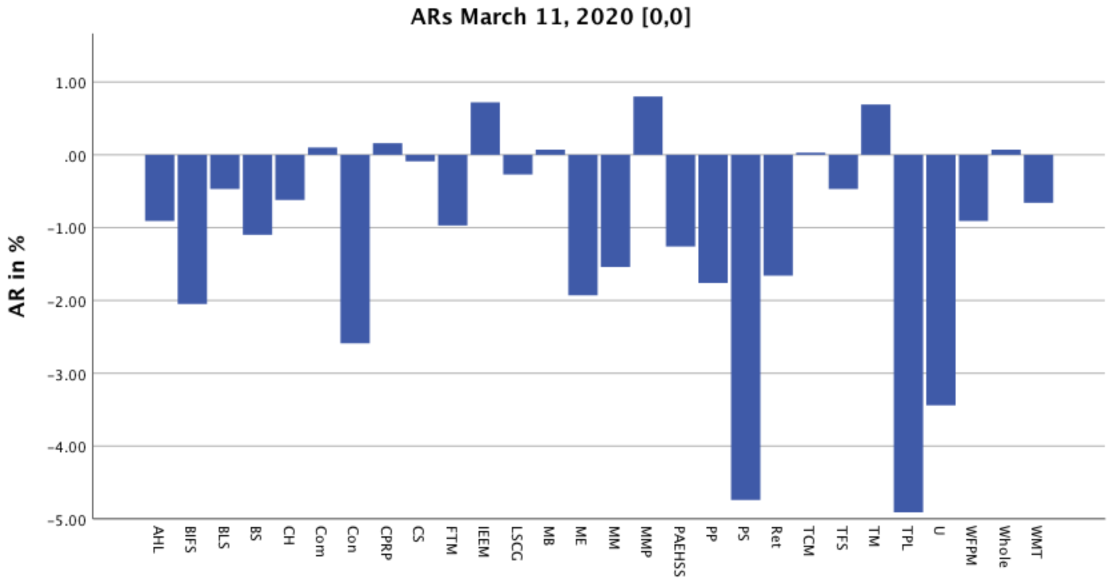

Figure 5c: The sectoral ARs on event date 3 [0,0]

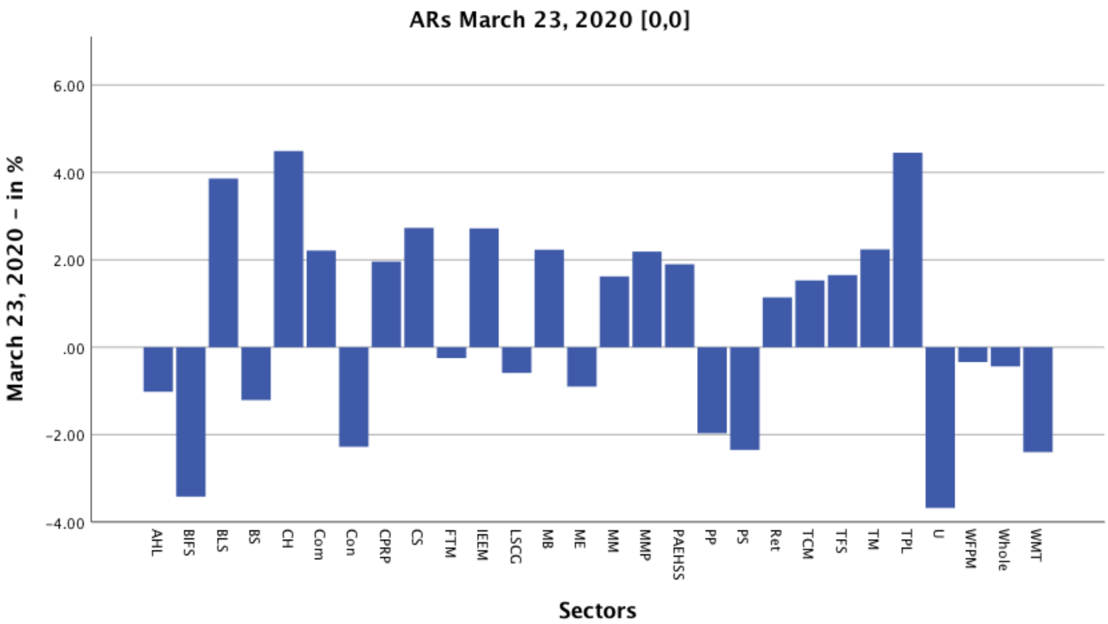

Figure 5d: The sectoral ARs on event date 4 [0,0]

experience positive abnormal returns. The second event requires a more closer look, because the majority of the sectors experience positive abnormal returns, however, the negative returns are stronger. The sector Mining and Extraction (ME) is the most negatively impacted sector on the first two events, whereas the sectors Property Services (PS), Travel, Personal and Leisure (TPL) and Utilities (U) are the most impacted sectors on event 3. The pattern of the positive impacted sectors is less clear, and will be further researched with the different event windows.

6. Results & discussion

The results consist of three main parts. The first, and largest part of this research is the event analysis. Then, the post-event analysis will be briefly highlighted and finally to test for control variables, a regression analysis was performed.

6.1 Event analysis

For the event analysis, a one sample t-test was executed in SPSS. However, before the one sample t-test can be executed, first the assumptions for conducting a one sample t-test should be assessed. After the assumptions are assessed, the four events will be tested, and results will be analysed and finally, the hypotheses will be answered.

6.1.1 Assumptions for one sample t-test

Before the one sample t-tests can be executed, it is important to know whether the assumptions for the student's t-test are met, in order to be able to validate the results. There are three assumptions which require attention: the independence assumption, the sample size assumption and the normality assumption.

First, the independence assumption. This entails that the sample data is independent from each other. Even though this is an important assumption, it cannot be tested (De Veaux, Velleman, & Bock, 2016). Since the data that has been used is stock data, the independence can be assumed.

Second, the sample size assumption. To reduce sampling error, it is important to have a good representation of the population (Babbie, 2016). This can be achieved by random sampling, and, with a large sample size, because the larger the sample size, the more likely it represents the population (Babbie, 2016). Random sampling has not been applied, however, this sample consists of 4112 individual companies, which represent 28 BvD sectors. This can be assessed as a large sample size. Nevertheless, it is important to consider, that not all sectors contain an equally large representation of these individual companies (Appendix A, table 1). For instance, the AHL sector represents 8 companies, whereas the BIFS represents 935 companies.

Finally, the normality assumption, for which the dependent variables are required to have a nearly normal condition (De Veaux et al., 2016). According to the Central Limit Theorem, normality can be assumed for sample sizes of 30 or higher (Field, 2018). The majority of the sectors, have a sample size larger than 30, so for these sectors, normality can be assumed. Nevertheless, there are seven sectors, which do not have a sample size of 30 or higher. For these sectors, the normality should be tested. Since the sample sizes are larger than 30, it is appropriate to apply the Shapiro-Wilk test to test for normality. The test has been performed in SPSS. The null hypothesis of a Shapiro-Wilk test indicates that the data is normally distributed. So, for a 95% significance test, when the significance outcome of SPSS is below 0.05, it means that the null hypothesis is rejected and that the data is not normally distributed. Appendix B table 1-4 provide the results of the Shapiro-Wilk test for each event and the accompanying event windows. This shows that only the AHL sector appears to have a normal distribution across all event dates and windows. For the other six sectors (CH, LSCG, MM, PP, TCM, WMT), normality cannot be assumed since the null hypothesis has been rejected in one or more events. This problem could be solved by removing outliers. However, since this event study is about finding abnormal returns, it could bias the data. Similarly, Sorokina, Booth, and Thornton (2013) researched the effect of outliers on the results of event studies by analysing existing event studies regarding US stock markets. These results show that outliers are common within event studies, however, are preferably not removed since these outliers contain important information for the purpose of event studies (Sorokina et al., 2013). Since most sectors consist of a nearly normal distribution, and removing outliers could provide biased results, this study will continue with the original data. However, to improve robustness, for the six sectors of which normality cannot be assumed, an additional non-parametric test was performed: the Wilcoxon Signed Rank Test. Therefore the following formula is applicable:

$$W = \sum_{i=1}^{N_r} [sgn(x_{2,i} - x_{1,i})\, R_i]$$

The test was executed in SPSS and the significance was tested with help of the z-score:

$$Z = \frac{T - \bar{T}}{SE_{\bar{T}}}$$

The results of this Wilcoxon Signed Rank Test are provided in Appendix C table 1-4, and these confirm the results of the t-test.

To summarize, the assumptions are not perfectly met, however, it provided sufficient information to continue the student's t-test and consider the limitations. To minimalize this impact and increase robustness, the Wilcoxon Signed Rank Test was performed on the sectors for which normality cannot be assumed. The results of the Wilcoxon Signed Rank test confirm the results of the t-test and thus these results can be applied.

6.1.2 Event 1

Starting with the results of event 1: January 21, 2020, the date that the first COVID-19 patient was discovered in the United States. Table 5 displays that there are many sectors which experienced significant abnormal returns. First, analysing at the average Cumulative Abnormal Returns of all sectors combined, the average abnormal return is declining when the even window increases, -1.2% for [-3,3], -0.7% [-5,5] and -3.0% for [-10,10]. Additionally, the average standard deviation increases as well from 7.3%, to 9.9% to 14.4%. Similarly, when comparing the average abnormal returns of the event date [0,0], -0.3% (Appendix A table 2) to the other event windows, the average CARs are indeed declining. This could indicate that the market does not immediately respond to the publicly available information and therefore would reject the efficient market hypothesis.

Next, the sectoral returns. Most abnormal returns in table 5 are negative, however, there are three sectors with at least two significant positive abnormal returns in the event windows: Communications, Construction and Utilities. All three sectors experienced a significant positive abnormal return during the event window [-3,3] and [-5,5], however not during the event window [-10,10]. So, these sectors could have had positive abnormal returns because these sectors performed better compared to others. Nevertheless, it could also be the case that these sectors experienced a delay in the reflection of new information on the share prices. The sectors experienced the following mean returns: +1.3% [-3,3] and +2.3% in [-5,5] for the sector Communications, +2.7% [-3,3] and +4.3% [-5,5] for the sector Construction and +2.3% [-3,3] and +2.9% [-5,5] for the sector Utilities. Comparing this to existing literature, first communications and construction, which both have not been mentioned in existing literature regarding the sectoral abnormal returns during COVID-19. The sector Constructions however, was highlighted in the research of Chilean natural disasters, where construction also experienced positive returns (Ruiz & Barrero, 2014). Nevertheless, during the natural disasters, the construction possibly experienced positive returns since many objects required rebuilding because of destruction (Ruiz & Barrero, 2014). This is not the case during COVID-19. Moreover, the Utilities sector, Panyagometh (2020) found that the sector Utilities experienced negative returns during COVID-19 in Thailand, whereas table 5 shows that the sector Utilities experienced significant positive result. This difference can be caused by several reasons. First, the study of Panyagometh (2020) was conducted in Thailand, and the sample consisted of only 46 companies compared to the 4112 companies within this study. These results are based on the event of the first COVID-19 patients in the US, whereas Panyagometh (2020) applied the event date of the pandemic announcement of the WHO. So, to retrieve a better comparison, the study of Panyagometh (2020) can better be compared to the results of event 3 of this paper.

In addition, there are many sectors with negative abnormal returns during this event. Therefore, only the sectors which have experienced significantly negative abnormal returns in all three event windows will be discussed: Banking Insurance & Financial Services, Business Services, Metals & Metal Products, Mining & Extraction, Textiles, Clothing Manufacturing, Transport, Freight & Storage and Wholesale. First, the Banking, Insurance & Financial service sector, which experienced an abnormal return of -0.3% in [-3,3], -0.4% in [-5,5] and -0.9% in [-10,10]. The negative abnormal returns in this sector is in line with the results of Panyagometh (2020) in the COVID-19 research in Thailand. According to Panyagometh (2020), the negative impact on the banking sector has been caused by the financial impact of COVID-19 on the business and household sectors. This claim can be supported by the negative abnormal returns on the Business Service sector within this study: -1.1% in [-3,3], -1.3% in [-5,5] and -4.0% in [-10,10]. Again this was confirmed already by Panyagometh (2020), which can be explained by the lockdown and the forced closure of businesses for a period of time (H. C. Chen & Yeh, 2021). However, there were also businesses which have benefited from the pandemic, for instance businesses in healthcare, tech and pharmaceutical subsectors, and the businesses which were excluded from the forced closure, for instance supermarkets like the 7-eleven, this possibly has caused the high volatility within this sector (Panyagometh, 2020).

Continuing with the sector Metals & Metal Products, which experienced abnormal returns of -3.3% in [-3,3], -2.2% in [-5,5] and -5.0% in [-10,10], and the sector Mining & Extraction: -10.7% in [-3,3], -12.8% in [-5,5] and -20.9% in [-10,10]. The sector Metal & Metal Products shows an abnormal return of -3.3.% in [-3,3] and -5.0% in [-10,10]. The sector Mining & Extraction experienced a significant abnormal return of -10.7% in [-3,3], -12.8% in [-5,5], and -20.9% in [-10,10]. So, these abnormal returns appear to decrease more over time. Table 5 shows that the mining sector experienced the strongest abnormal returns during this event. In China, around the event date January 23, 2020, the mining sector also experienced strong negative abnormal returns (He et al., 2020). According to He et al. (2020), this is caused since mining is very reliant on transportation and since that was hindered during this period, so, the mining suffered from it as well. Within this study, the sector Transport, Freight & Storage indeed also experienced negative abnormal returns: -6.2% in [-3,3], -7.3% in [-5,5], and -13.9% in [-10,10].So, this indeed could indicate that the theory of He et al. (2020) is correct, that the negative returns of the Mining & Extraction sector could be connected to the negative returns of the Transport, Freight & Storage sector.

Finally, the sectors Textiles & Clothing Manufacturing and Wholesale. The sector Textiles & Clothing Manufacturing experienced significant abnormal returns of -2.3% in [-3,3], -3.9% in [-5,5] and -10.8% in [-10,10]. Interestingly, is that the sector manufacturing experienced positive abnormal returns in a Chinese study (He et al., 2020). Nonetheless, this is an overall sector of Manufacturing, whereas Textiles & Clothing Manufacturing is only one subpart. The sector Wholesale experienced abnormal returns of -1.6% in [-3,3] and [-5,5] and -5.3% in [-10,10]. Interestingly, is whether these sectors possibly have impacted each other. For instance, could the Wholesale sector have negative abnormal returns because manufacturing is negatively impacted and cannot deliver its products? There is no prior research confirming this idea, however, this is an interesting topic for future research.

To summarize, there are three sectors with significantly positive abnormal returns in two event windows, and seven sectors with significantly negative abnormal returns in all three event windows. Most of the results of these sectors are in line with current literature except for the sector Utilities and Manufacturing.

Table 5

CAR of the sectors of event date 1: January 21,2020

BvD 28 sectors		[-3,3]			[-5,5]			[-10,10]		
	Df	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	-2.4%	4.7%	-1.45	-1.3%	8.0%	-0.44	-2.0%	7.8%	-0.72
BIFS	934	-0.3%	3.3%	-2.44*	-0.4%	3.8%	-3.27***	-0.9%	5.6%	-5.03***
BLS	171	-0.1%	24.2%	-0.07	2.7%	37.3%	0.94	5.1%	45.7%	1.47
BS	500	-1.1%	5.3%	-4.44***	-1.3%	6.0%	-4.94***	-4.0%	11.1%	-8.05***
CPRP	357	-3.0%	12.5%	-4.48***	-2.4%	18.2%	-2.45*	-2.1%	30.4%	-1.29
Com	91	1.3%	6.7%	1.89*	2.3%	8.0%	2.76***	-0.8%	13.3%	-0.58
CH	26	0.8%	8.2%	0.48	1.1%	10.7%	0.53	-2.0%	9.1%	-1.13
CS	104	-0.5%	7.1%	-0.70	0.6%	9.2%	0.68	3.3%	16.3%	2.08*
Con	48	2.7%	6.7%	2.78***	4.3%	8.9%	3.34***	-0.2%	10.1%	-0.13
FTM	63	-1.2%	7.4%	-1.27	-1.4%	8.4%	-1.37	-4.8%	10.8%	-3.57***
IEEM	528	0.3%	10.9%	0.56	0.9%	17.5%	1.16	0.2%	23.3%	0.20
LSCG	11	-1.9%	5.2%	-1.27	-1.4%	5.3%	-0.92	3.1%	16.3%	0.66
MB	72	-2.0%	7.5%	-2.30*	-0.6%	7.3%	-0.72	-0.9%	11.8%	-0.67
MMP	76	-3.3%	5.9%	-4.91***	-2.2%	7.6%	-2.53*	-5.0%	9.8%	-4.51***
ME	97	-10.7%	8.3%	-12.78***	-12.8%	9.9%	-12.83***	-20.9%	15.4%	-13.45***
MM	16	-0.6%	4.0%	-0.64	0.6%	7.4%	0.36	1.6%	17.2%	0.39
PP	18	-1.7%	4.4%	-1.67	-1.6%	7.0%	-0.97	-6.2%	11.2%	-2.41*
PS	201	1.1%	3.4%	4.81***	1.6%	4.6%	5.01***	0.1%	6.4%	0.12
PAEHSS	66	-0.1%	11.4%	-0.10	2.9%	12.7%	1.85*	2.8%	15.8%	1.47
Ret	132	-1.2%	7.9%	-1.69*	-0.1%	9.5%	-0.13	-3.2%	13.2%	-2.79***
TCM	26	-2.3%	5.1%	-2.32*	-3.9%	10.2%	-2.00*	-10.8%	11.9%	-4.71***
TM	76	-0.3%	7.2%	-0.39	-0.2%	8.8%	-0.25	-2.8%	14.4%	-1.73*
TFS	128	-6.2%	8.2%	-8.61***	-7.3%	11.5%	-7.25***	-13.9%	18.5%	-8.51***
TPL	116	-1.0%	6.5%	-1.65	-1.1%	8.0%	-1.49	-2.4%	11.1%	-2.37*
U	76	2.3%	5.5%	3.64***	2.9%	7.1%	3.60***	1.2%	11.1%	0.98
WMT	10	-1.2%	7.1%	-0.55	-0.8%	10.2%	-0.26	-8.4%	14.9%	-1.88*
Whole	86	-1.6%	5.7%	-2.68***	-1.6%	7.3%	-2.07*	-5.3%	9.6%	-5.17***
WFPM	48	-0.4%	4.5%	-0.64	0.5%	6.4%	0.56	-4.5%	11.7%	-2.69*
Average		-1.2%	7.3%	-1.53125	-0.7%	9.9%	-0.83	-3.0%	14.4%	-2.29

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

6.1.3 Event 2

The results of the second event, the day that the US declares a public health emergency on February 3, 2020 are displayed in table 6. The average abnormal return for all sectors are -2.0% for the event window [-3,3], 3.3% for [-5,5] and -4.0% for [-10,10]. In addition, all event windows have many negative abnormal returns, for this event, there is no reason to believe that there is a delay in information reflected in the share prices.

In comparison to event 1, there is only one sector which experienced a significant positive abnormal return in one event window: the sector Utilities in event window [-10,10], +1.8%. Nevertheless, the event window [-3,3] and [-5,5] show negative (insignificant) abnormal returns, and since the event window [-10,10] overlaps with event 1, there is reason to believe that this has caused the positive abnormal return. Additionally, the sectors Communication and Construction, which experienced significant positive results during event 1, now experienced significant negative abnormal returns. This could confirm the prediction that these sector not immediately reflected all the information of COVID-19 in their share prices.

Similarly as for the previous event, all the seven sectors which experienced significant negative abnormal returns in all three event windows are discussed. First of all, all the sectors with negative abnormal returns which have been discussed in with event 1, also experienced significant abnormal returns during event 2. In addition to those sectors, there are six other sectors which experienced significant abnormal returns during event 2: Chemicals, Petroleum, Rubber & Plastic, Computer Hardware, Food &Tabaco Manufacturing, Industrial, Electric & Electronic Machinery, Retail and Wood, Furniture & Paper Manufacturing.

First, the sector Chemicals, Petroleum, Rubber & Plastic, which experienced abnormal returns of -1.5% in [-3,3], -2.3% in [-5,5] and -5.8% in [-10,10]. Second, the sector Computer Hardware, which experienced a significant abnormal return of -3.8% in [-3,3] and -4.9% in [-5,5] and -5.2% in [-10,10]. This is rather similar to the literature, Chen and Yeh (2021) for instance, also ranked both sectors relatively high in how strong these were impacted by COVID-19. Computer hardware was ranked 11 out of 49 and Chemicals was ranked 14 out of 49. Third, the sector Industrial, Electric, & Electronic Machinery (IEEM) has a significant abnormal return of -2.8% in [-3,3], -3.4% in [-5,5], and -3.3% in [-10,10]. This is a difficult sector to compare, since it exists of multiple components however, in the study of Goodell and Huynh (2020), the three sectors Machinery, Electrical Equipment, and Electronic Equipment seem to come close to the IEEM sector. These sectors however, do not show significant abnormal returns, except for Electronic Equipment, but only on the event date of February 26, 2020 [0,0]. So, this difference is likely be caused by the difference between the composition of the sectors, and the different event windows.

Continuing, the sector Retail has a significant cumulative abnormal return of -2.4% in [-3,3], -4.3% in [-5,5] and -5.3% in [-10,10], the sector Food & Tabaco Manufacturing -2.2% in [-3,3], -2.4% in [-5,5], and -3.3% in [-10,10] and the sector Wood, Furniture & Paper Manufacturing -3.3% in [-3,3], -4.9% in [-5,5] and -6.8% in [-10,10]. So, all the abnormal returns seem to increase over time. Similarly to what has been mentioned in event 1, it is interestingly to know whether the Manufacturing sectors have influenced the negative returns of the retail. Besides this, the Retail sector could also have experience negative abnormal returns due to the restrictions implemented by the government, for instance, the lock down and closure of restaurants and shops (Baker et al., 2020).

To summarize, in addition to the six sectors which already were impacted in event 1, there are an additional six sectors which have experienced significant negative abnormal returns during all three event windows in the event of February 3, 2020. So the total number of sectors that have been negatively impacted in all three event windows is increased to thirteen.

Table 6

CAR of the sectors of event date 2: February 3, 2020

BvD 28 sectors		[-3,3]			[-5,5]			[-10,10]		
	Df	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	0.6%	5.9%	0.27	-0.6%	3.6%	-0.51	-0.2%	3.9%	-0.12
BIFS	934	-0.2%	3.5%	-2.00**	-0.8%	4.4%	-5.45***	-0.9%	5.8%	-4.75***
BLS	171	-1.8%	12.1%	-2.01**	-1.3%	20.8%	-0.82	-2.0%	45.7%	-0.57
BS	500	-1.7%	4.6%	-8.12***	-2.5%	5.9%	-9.53***	-4.2%	8.3%	-11.29***
CPRP	357	-1.5%	12.7%	-2.21**	-2.3%	19.4%	-2.28**	-5.8%	28.1%	-3.91***
Com	91	-3.9%	11.7%	-3.19***	-3.5%	13.3%	-2.52**	-2.3%	16.8%	-1.30
CH	26	-3.8%	5.3%	-3.77***	-4.9%	6.0%	-4.19***	-5.2%	11.2%	-2.43**
CS	104	0.4%	9.2%	0.50	0.6%	10.1%	0.62	0.3%	12.7%	0.21
Con	48	-3.6%	5.6%	-4.48	-2.7%	6.5%	-2.93***	-0.8%	8.9%	-0.66
FTM	63	-2.2%	5.1%	-3.51***	-2.4%	6.6%	-2.89***	-3.3%	10.7%	-2.46**
IEEM	528	-2.8%	8.5%	-7.51***	-3.4%	14.2%	-5.46***	-3.3%	21.0%	-3.59***
LSCG	11	2.8%	13.2%	0.74	0.7%	12.9%	0.18	0.4%	15.5%	0.10
MB	72	-0.1%	7.3%	-0.15	-0.6%	7.8%	-0.61	-3.4%	11.1%	-2.62**
MMP	76	-1.1%	5.9%	-1.60	-2.5%	7.6%	-2.91***	-5.5%	11.4%	-4.26***
ME	97	-3.4%	9.8%	-3.45***	-9.5%	11.3%	-8.38***	-18.6%	14.4%	-12.83***
MM	16	-5.6%	10.4%	-2.25**	-9.5%	14.8%	-2.65**	2.7%	64.2%	0.17
PP	18	-0.1%	7.0%	-0.04	-2.2%	7.5%	-1.28	-4.2%	9.1%	-2.00*
PS	201	-0.7%	3.4%	-2.91***	-0.5%	4.2%	-1.84*	0.2%	6.3%	0.49
PAEHSS	66	-0.7%	6.7%	-0.84	-1.0%	10.5%	-0.78	-1.4%	16.1%	-0.72
Ret	132	-2.4%	5.2%	-5.46***	-4.3%	7.8%	-6.34***	-5.3%	11.5%	-5.29***
TCM	26	-5.0%	6.2%	-4.16***	-9.4%	10.0%	-4.91***	-10.8%	13.4%	-4.17***
TM	76	0.4%	9.5%	0.41	-2.2%	10.8%	-1.83*	-2.9%	14.0%	-1.79
TFS	128	-6.4%	10.3%	-7.07***	-10.1%	13.1%	-8.75***	-14.7%	17.8%	-9.42***
TPL	116	-0.2%	6.2%	-0.33	-0.9%	7.5%	-1.35	-0.8%	11.6%	-0.75
U	76	-0.4%	5.3%	-0.64	-0.9%	5.5%	-1.41	1.8%	9.0%	1.78*
WMT	10	-5.7%	11.5%	-1.62	-6.5%	15.8%	-1.37	-8.3%	15.5%	-1.78
Whole	86	-2.7%	5.8%	-4.43***	-4.5%	7.7%	-5.50***	-7.6%	10.8%	-6.55***
WFPM	48	-3.3%	8.1%	-2.89***	-4.9%	9.7%	-3.55***	-6.8%	12.1%	-3.91***
Average		-2.0%	7.7%	-2.60	-3.3%	9.8%	-3.19	-4.0%	15.6%	-3.01

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

6.1.4 Event 3

The third event, is a date that has been implemented in many other studies as well and represent the date that the WHO declared the COVID-19 a pandemic, March 11, 2020 (H. C. Chen & Yeh, 2021; Panyagometh, 2020). Table 7 displays the cumulative abnormal returns of the sectors, and so far, this event appears to have the highest number of sectors which show significant abnormal returns. Moreover, the average CARs of all sectors together are the highest as well. In contrast to the first two events, the event window [-5,5] is impacted the hardest with -21.7%, event window [-3,3] with -11.5% and event window [-10,10] with -9.3%. Interestingly, is that the longest event window decrease, this could indicate that the returns are recovering. For instance, the sector Chemicals, Petroleum, Rubber & Plastic, experienced significant negative returns during the previous event, experienced significant negative returns during the first two event windows of this event: -6.6% [-3,3] and -8.6% in [-5,5], however, experienced positive significant abnormal returns during the last event window, 5.1% [-10,10]. This difference should thus be caused by positive returns in the future.

Continuing, when analysing the sectoral results, again, all seven sectors which have been outlined in event 1 and 2, again have negative abnormal returns in all three event windows of event three: BIFS, BS, MMP. ME TCM, TFS and Wholesale. In addition to that, the following three sectors which have been outlined in event 2, also experienced negative abnormal returns in all three event windows of event 3: Retail, WFPM and Construction. Moreover, there are five new sectors which have experienced significant negative abnormal returns in all three windows: Leather, Stone, Clay & Glass products, Property Services, Transport Manufacturing, Travel, Personal & Leisure, and Utilities. The two most impacted sectors during this event, and the two previous events are Property Services, -27.8% in [-3,3], -44.0% in [-5,5] and -29.5% in [-10,10], and Travel, Personal & Leisure, -26.5% in [-3,3], -52.7% in [-5,5] and -23.0% in [-10,10].

Property Services has not been mentioned in previous literature, however, Travel, Personal & Leisure has. This is in line with the findings of Griffith, et al. (2020), who researched the sectoral stock return in the UK during COVID-19. These abnormal returns are possibly been influenced by the air-travel restrictions that have been implemented in the US on February 2nd [18] (Griffith et al., 2020). Interestingly then however, is that this is not reflected in the cumulative abnormal returns of event 2, even though event 2 is on February 3rd, this could again indicate that there is a delay in the reflection of available information in the share prices, which would confirm the Behavioural Finance theory.

To summarize, the abnormal returns among the event date March 11, 2020, are more severe than the other event dates. First, the abnormal returns are larger and there are stronger average abnormal returns. Second, there are more sectors that have negative abnormal returns, and thus are negatively impacted by the event. The sectors that have been impacted the most are the Travel, Personal & Leisure and Property Service sectors. Additionally, the abnormal returns seem to increase again during the event window [-10,10, this difference between the event windows [-5,5] and [-10,10] could indicate that there is a recovery, which can be discovered by analysing the results of event 4.

18 AJMC (January 1, 2021) A timeline of COVID-19 Developments in 2020 Retrieved from: https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020

Table 7

CAR of the sectors of event date 3: March 11, 2020

BvD 28 sectors		[-3,3]			[-5,5]			[-10,10]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	-11.7%	18.8%	-1.77	-15.6%	19.4%	-2.28*	-4.6%	16.6%	-0.79
BIFS	934	-14.7%	15.3%	-29.42***	-27.5%	27.1%	-31.04***	-16.0%	20.9%	-23.52***
BLS	171	-15.0%	24.3%	-8.06***	-15.2%	28.4%	-7.02***	3.3%	38.0%	1.15
BS	500	-10.3%	15.3%	-14.99***	-18.0%	23.4%	-17.20***	-15.2%	20.3%	-16.72***
CPRP	357	-6.6%	34.5%	-3.63***	-8.6%	38.6%	-4.21***	5.1%	44.0%	2.19**
Com	91	-6.3%	15.6%	-3.86***	-11.9%	21.2%	-5.39***	-3.3%	23.2%	-1.36
CH	26	-11.3%	27.4%	-2.14**	-21.2%	43.4%	-2.53**	-5.0%	32.7%	-0.80
CS	104	-5.6%	18.0%	-3.18***	-13.5%	25.5%	-5.43***	-1.7%	21.0%	-0.81
Con	48	-24.9%	24.2%	-7.20***	-36.4%	33.0%	-7.73***	-15.5%	19.2%	-5.65***
FTM	63	-3.4%	17.6%	-1.56	1.1%	45.0%	0.19	0.0%	42.4%	0.01
IEEM	528	-6.0%	22.3%	-6.18***	-11.3%	32.2%	-8.08***	0.5%	37.3%	0.30
LSCG	11	-12.0%	16.7%	-2.48**	-31.0%	30.6%	-3.50***	-13.2%	14.8%	-3.09**
MB	72	-2.4%	21.9%	-0.95	-9.3%	43.5%	-1.82	2.3%	43.3%	0.45
MMP	76	-4.4%	17.2%	-2.23**	-13.7%	25.3%	-4.75***	-5.3%	21.8%	-2.12**
ME	97	-19.9%	32.6%	-6.05***	-39.3%	42.4%	-9.17***	-22.8%	30.8%	-7.32***
MM	16	-12.3%	23.7%	-2.13**	-22.7%	33.7%	-2.78**	-11.9%	29.6%	-1.66
PP	18	0.8%	20.0%	0.18	-16.6%	27.2%	-2.66**	-13.6%	20.9%	-2.83**
PS	201	-27.8%	18.1%	-21.82***	-44.0%	28.9%	-21.60***	-29.5%	23.5%	-17.86***
PAEHSS	66	-15.1%	33.5%	-3.68***	-26.2%	40.7%	-5.27***	-8.7%	46.0%	-1.55
Ret	132	-10.1%	21.8%	-5.36***	-19.7%	36.0%	-6.31***	-6.4%	28.7%	-2.59**
TCM	26	-14.0%	12.3%	-5.93***	-26.0%	24.9%	-5.42***	-14.3%	20.3%	-3.66***
TM	76	-5.3%	19.0%	-2.45**	-21.8%	26.1%	-7.33***	-8.2%	33.1%	-2.18**
TFS	128	-6.4%	27.8%	-2.59**	-24.1%	40.6%	-6.75***	-10.0%	34.2%	-3.32***
TPL	116	-26.5%	26.1%	-11.00***	-52.7%	38.7%	-14.74***	-23.0%	26.2%	-9.51***
U	76	-15.1%	21.6%	-6.14***	-9.0%	26.4%	-3.01***	-13.6%	21.2%	-5.65***
WMT	10	-12.9%	21.4%	-2.00*	-28.0%	25.6%	-3.62***	-8.6%	28.7%	-1.00
Whole	86	-13.3%	26.1%	-4.75***	-24.5%	41.1%	-5.57***	-10.9%	24.4%	-4.19***
WFPM	48	-9.8%	14.4%	-4.76***	-21.6%	23.5%	-6.44***	-10.6%	18.2%	-4.10***
Average		-11.5%	21.7%	-5.93	-21.7%	31.9%	-7.19	-9.3%	27.9%	-4.22

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

6.1.5 Event 4

The fourth and final event date that is analysed during this research is event 4: the day that the federal reserve pledges to support the economy under any circumstances, March 23, 2020. Table 8 provides an overview of the cumulative abnormal returns for this event date. The event window of [-10,10] for this event has been deleted since this one overlaps with event 3. Interestingly, is that during the the average abnormal return of all sectors for both event windows is positive for the first time: +7.0% in [-3,3] and +1.2% in [-5,5].

So, interestingly, is that after this event, most sectoral experienced significant positive CARs, even though nothing has changed about the severity and seriousness of the COVID-19 virus. What has changed, is the fact that the federal reserve has pledged to support the economy. This could be an example of the behavioural finance theory, then the pledge of the federal reserve, has increased the trust of investors and therefore share prices started to increase again instead of decreasing.

Table 8

CAR of the sectors of event date 4: March 23, 2020

BvD 28 sectors		[-3,3]			[-5,5]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	2.6%	12.3%	-0.44	-1.9%	12.3%	0.60
BIFS	934	4.7%	12.5%	11.45***	-2.1%	11.9%	-5.49***
BLS	171	12.3%	33.8%	4.76***	12.3%	33.1%	4.87***
BS	500	-0.2%	14.5%	-0.30	-2.0%	13.7%	-3.26***
CPRP	357	7.6%	18.6%	7.76***	7.7%	20.8%	7.03***
Com	91	4.6%	16.7%	2.66***	6.1%	16.8%	3.47***
CH	26	15.3%	31.4%	2.53**	4.8%	27.1%	0.92
CS	104	7.1%	17.3%	4.22***	5.3%	14.7%	3.66***
Con	48	16.0%	22.5%	4.97***	-1.3%	16.3%	-0.57
FTM	63	0.6%	22.1%	0.22	8.7%	35.8%	1.94*
IEEM	528	6.8%	20.8%	7.52***	6.5%	24.5%	6.10***
LSCG	11	5.9%	13.6%	1.51	-3.0%	12.8%	-0.81
MB	72	11.1%	29.5%	3.22***	6.9%	39.4%	1.50
MMP	76	1.5%	10.3%	1.25	0.2%	17.9%	0.08
ME	97	6.3%	27.2%	2.29**	-4.2%	22.2%	-1.88*
MM	16	6.8%	21.2%	1.32	9.5%	29.1%	1.35
PP	18	-4.6%	18.8%	-1.08	-12.2%	18.7%	-2.84**
PS	201	8.3%	22.0%	5.36***	-7.5%	20.6%	-5.18***
PAEHSS	66	12.6%	16.4%	6.29***	3.1%	20.2%	1.26
Ret	132	7.6%	19.5%	4.49***	-2.5%	20.7%	-1.39
TCM	26	4.8%	17.9%	1.40	-5.5%	16.9%	-1.68
TM	76	8.5%	30.0%	2.50**	-3.4%	30.0%	-0.98
TFS	128	5.8%	16.5%	4.00***	1.8%	33.5%	0.60
TPL	116	23.2%	27.3%	9.17***	-1.8%	19.8%	-1.00
U	76	-1.7%	12.4%	-1.20	3.5%	12.3%	2.50***
WMT	10	10.0%	13.5%	2.45**	2.7%	16.3%	0.56
Whole	86	9.2%	21.6%	3.99***	2.1%	18.7%	1.05
WFPM	48	3.8%	18.9%	1.40	-1.2%	14.6%	-0.58
Average		7.0%	20.0%	3.35	1.2%	21.1%	0.42

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

6.1.6 Hypothesis 1

Now that the abnormal returns of all four events have been analysed and discussed, the hypotheses can be analysed and answered. The first hypothesis that will be discussed is:

Hypothesis 1: "*Between January 21, 2020 (the first COVID-19 patient in the US) and March 23, 2020 (pledge of the federal reserve to support the economy), the average of all sectors on the US stock market, will experience a significant abnormal decrease in the stock returns.*"

To answer this hypothesis, a summary of all the average CARs of all sectors is created in table 9. First of all, the first three events have negative abnormal returns in all event windows whereas event four has positive abnormal returns in the event windows. This already confirms hypothesis 1. This indicates prove for the behavioural finance theory as well. Because even though nothing has changed regarding the COVID-19 virus (there is no vaccine or cure), share prices increased again. It is likely, that this is because investors regained trust in the US economy after the pledge of the Federal Reserve on March 23, 2020.

Table 9

Summary of the CARs of all companies for the four events

	[0,0]		[-3,3]		[-5,5]		[-10,10]	
	Mean	*T-test*	*Mean*	*T-test*	*Mean*	*T-test*	*Mean*	*T-test*
Event 1	-0.2%	-2.79***	-0.98%	-6.94***	-0.6%	-3.16***	-2.1%	-7.40***
Event 2	-0.1%	-2.07**	-1.59%	-13.27***	-2.5%	-14.40***	-3.5%	-12.59***
Event 3	-1.1%	-12.43***	-11.78%	-33.30***	-21.2%	-40.81***	-9.6%	-19.76***
Event 4	0.0%	0.17	6.21%	20.08***	1.3%	20.08***		

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Additionally, when looking closer to the average CARs of the different event windows, we can indicate whether the efficient market hypothesis is applicable. Ass discussed in section 2.1, according to the efficient market hypothesis, the stock prices should adjust to new information on the event day self [0,0] and the day after (Brealey et al., 2020). However, to take pre-event leakage into consideration, event window [-

3,3] is also considered within the time period to accept the efficient market hypothesis. The cumulative abnormal returns of event 1-3 all seem to decrease even more, even after the event window of [-3,3]. This would indicate that the efficient market hypothesis is rejected: the market takes a while before the information is reflected within the share prices. Only for event 4, the grow during event window [-3,3] is flattened already during event window [-5,5], so based on this information, for event 4, hypothesis 1 should be rejected.

6.1.7 Hypothesis 2

The second hypothesis consists of two parts, first hypothesis 2a will be answered:

Hypothesis 2a: The sectors of Manufacturing, the Public Administration, Education and Health Social Services and the Biotechnology and Life Sciences will perceive positive abnormal returns during the first three events of COVID-19

For the first three events, there are 3 sectors which have experienced significant positive abnormal returns, which are Communications, Construction and Utilities. So, this part of the hypothesis is rejected. These are none of the sectors which have been hypothesised. So, this first part of the hypothesis is rejected. Then, the second part:

Hypothesis 2b: The sectors Banking, Insurance, & Financial Services, Transport, Freight & Storage, Travel, Personal & Leisure and Utilities experience negative abnormal returns during *the first three events of COVID-19*

For the second part of the analysis, every sector will separately be discussed. First, Banking, Insurance, & Financial Services (BIFS). This sector did experienced significant negative abnormal returns during all three events for all event windows. So, this is in line with the hypothesis. Then the sector Transport, Fright, & Storage, similarly, this sector also experienced significant negative abnormal returns during all three events and within all event windows. This as well, is thus in line with the hypothesis. Third, Travel, Personal & Leisure, this sector only experienced significant negative abnormal returns in all event windows in the third event. So, this is not entirely in line with the hypothesis. However, it is important to notice that this is one of the two sectors who have been impacted the most during all event dates. Finally, the sector Utilities, which had, as mentioned before, significant positive abnormal returns during the first two events, however, experienced negative significant results during the third event. Similarly, this is not in line with the hypothesis.

So, part of the hypothesis is confirmed, and partly not. Besides that, there are more sectors which experienced significant abnormal returns during all three events, however these sectors have not been hypothesised. So, this again is not in line with the hypothesis. Since this study contains multiple event days and multiple event windows, it can differ significantly from existing literature.

To conclude, both parts of the hypothesis are rejected. There are no sectors which experienced positive significant abnormal returns during multiple events. Additionally, only the BIFS and TFS have experienced significant abnormal returns during all three events.

6.2 Post-event analysis

Since all four events are close to each other and the post-event analysis analyses the long term impact, only one event has been analysed, the event that experienced the highest abnormal returns: event 3. To find out whether COVID-19 has a long term impact on the stock market, and for how long this impact would last, the following event windows have been analysed: [0,20] [0,40] [0,60] [0,80] [0,100] [0,120] [0,140] [0,160] [0,180] [0,200] [0,220] [0,240]. The results are presented in Appendix D table 1-4.

First, looking at the average abnormal return of the event windows, event window [0,20] still has a negative average abnormal return of -4.1%, whereas for all the other event windows, this is positive. Similarly, in the first event window [0,20], there are still many sectors which experience negative abnormal returns. However, when you continue to event window [0,40] , then this has decreased. Only the sectors BIFS, BS and PS have experienced negative returns during the first two event windows. The abnormal returns of the sectors BIFS and BS have already turned positive in event window [0,60], whereas the sector PS has significant negative abnormal returns until event window [0,160]. This is the only sector which seems to be negatively impacted this long.

So, for the majority of the sectors, there is no negative long term impact of COVID-19. There are however, many sectors which experience positive significant abnormal returns in the post-event period. Whether this is caused by the COVID-19 is questionable.

6.3 Regression analysis

As a final analysis, the regression analysis was executed. This has been executed to control for other explanatory variables to increase the robustness of the study. Before executing the regression, several assumptions have to be checked.

6.3.1 Assumptions

Before executing a multiple regression, several assumptions have to be checked. Only once the assumptions are correct, the model can be generalized (Field, 2018). Therefore, first, the following assumptions have been controlled:

1. Linearity assumption
2. Independence assumption
3. Homoscedasticity assumption
4. Normality assumption
5. Multicollinearity

1. Linear assumption

The relationship between the dependent variable and independent variables should be linear, otherwise the results cannot be interpreted. To test whether the relationship between the independent variables and dependent variables are linear, a partial regression plot has been created (Appendix E). The partial regression plot does appear to have a pattern, nevertheless, some patterns are stronger than others. Linearity is assumed based on these patterns, however, this is disputable since not all partial regression plots show strong patterns.

2. Independence assumption

The second assumption that has to be met is the independence assumption. This means that the observations need to be independent from each other. Since the data that has been gathered is daily company share prices, this cannot be retrieved differently and therefore the independence assumption can only be assumed to be met.

3. Homoscedasticity assumption

Third, the homoscedasticity assumption should be controlled. This entails that the variance of the variables are equally distributed. This can be controlled with a scatterplot of the standardized residuals, these should be randomly distributed, so there should not be a visible pattern. This scatterplot is available in Appendix F. The scatterplot seems random however, there could be a small pattern identified. So homoscedasticity is assumed, however, it should be considered when analysing the results, that the homoscedasticity was questionable.

4. Normality Assumption

Then, the normality assumption has to be tested. The dependent variables should be normally distributed to be able to generalize the results. To test the normality assumption, both a PP-plot and a histogram are retrieved from SPSS, the results can be found in Appendix G. The dependent variables are somewhat normally distributed, however, as can be seen from the PP plots, they are a little skewed. This could also explain why they homoscedasticity assumption is a little doubtful (Field, 2018). However, since this research has a large sample size, the normality distribution is less important (Field, 2018).

5. Multicollinearity

Finally, the multicollinearity should be checked. This entails that the independent, or predictor variables should not highly correlated with each other. Because once the variables are too highly correlated, the standard error increases and therefore a Type II error can occur (Hair, Black, Babin, & Anderson, 2013). Since this needs to be prevented, the multicollinearity requires testing. This has been performed with a correlation matrix (table 10).

The correlation matrix in table 10 shows that the highest correlation is between the variable D/E ratio and market-to-book ratio (0.504). However, since this correlation is still below 0.7, there is no reason to delete one of the variables.

Table 10

Pearson Correlation Matrix

	[-5,5]	ROE	SIZE	D/E	MTB
CAR MARCH 11 [-5,5]	1.000	0.107	0.062	-0.034	0.088
ROE	0.107	1.000	0.103	0.108	0.118
SIZE	0.062	0.103	1.000	0.117	0.121
D/E	-0.034	0.108	0.117	1.000	0.504
MTB	0.088	0.118	0.121	0.504	1.000

6.3.2 Results

According to Field (2018), when there is existing literature available, concluding which predictor variables are stronger predicting the dependent variable, than this information should be considered when conducting a regression. Then, the most appropriate method is the hierarchal regression, and entering the independent variables with the strongest predictions first, and adding the variables with the least strong predictions last, especially when conducting exploratory research, which is the case for this regression analysis. Based on the results of the regressions of Xiong et al. (2020) and Al-Awadhi et al. (2020), first the ROE will be added, then SIZE, then LEV and finally the MTB.

Additionally, the handling of missing data requires outlining. Unfortunately, there is substantially missing data within the Orbis data set, therefore it is important to determine how this missing data is treated within the analysis. As mentioned before, for the event analysis, all the companies that missed daily share prices, have been excluded from the data set already. The same sample is used for the regression as well. However, with regards to the firm-specific information, there is also substantial amount of missing data within the Orbis data base. However, to prevent biased results, it is still decided to implement listwise deletion, which entails that when a companies has missing data, the entire case (company) is deleted from the data set. This resulted in a total sample size of 2383.

It is however important to consider, whether there is a reason why Orbis has this much of missing data. For instance, it could be the case that Orbis doesn't have data from the small companies, only from the larger ones. This is important to consider when analysing the results, since this could have caused some bias.

First, a regression analysis of the total data set will be provided to control for robustness, After that, the different firm-specific variables will be averaged per sector. This way, it can be determined whether the sectors with negative abnormal returns for instance have higher or lower ratios.

Before providing the results of the overall regression, the descriptive statistics are provided in Table 11.

Table 11

Descriptive Statistics regression analysis March 11, 2020

	Mean	Std. Deviation	N
CAR MARCH 11 [-3,3]	-0.09	0.21	2388
CAR MARCH 11 [-5,5]	-0.14	0.27	2388
CAR MARCH 11 [-10,10]	-0.09	0.41	2388
ROE 2020	-15.70%	86.49%	2388
SIZE 2020	13553	65729	2388
D/E ratio 2020	2.60	6.95	2388
MTB 2020	5.65	11.51	2388

So, the average Return of Equity of all companies is -15.7%, the average number of employees is 13.553, the average D/E ratio is 2.60 and the average MTB ratio is 5.65. Then, table 12 provides the results of the regression analysis. First, the variable ROE, which has a positive significant effect on the first two models. So, companies with a high Return on Equity are more likely to have a higher CARs in the event windows [-3,3] and [-5,5]. Then, the variable SIZE, which has a positive significant effect on the first two models as well. So, companies with more employees are more likely to have higher CARs during COVID-19. Third, the variable D/E ratio, which has a significant negative effect on all three models. So, companies with a lower D/E ratio, or lower level of leverage, overall have lower CARs. The last variable, MTB, has a positive significant effect on the CAR of all three models. So, when a stock has a higher value compared to its book value, the chance are increased on higher CAR. Finally, the adjusted R^2 is relatively low for all event windows, this indicates that the four dependent variables only explain a very small part of the results. For instance, only 3.1% of the CAR [-3,3] is explained by the four variables ROE, SIZE, D/E and MTB.

Table 12

Robustness tests using regression

	1	2	3
Variables	CAR [-3,3]	CAR [-5,5-]	CAR [-10,10]
ROE	0.111(5.461)***	0.100 (4.871)***	0.027 (1.331)
SIZE	0.045 (2.190)**	0.049 (2.411)**	0.029 (1.414)
D/E	-0.024 (-1.221)***	-0.115 (-4.886)***	-0.140(-5.941)***
MTB	0.138 (5.409)***	0.128 (5.452)***	0.155 (6.58)***
Constant	-0.091 (-18.409)***	-0.138(-21.550)***	-0.1 (-10.458)***
Observations	2383	2383	2383
Adj R^2	0.031	0.027	0.022

*Standardized betas and t-stat in parenthesis. Significance: *** at 1% level, ** at 5% level, * at 10% level.*

Table 13

Descriptive statistics for regression analysis sectors March 11, 2020 [-5,5]

		ROE in %		SIZE		D/E		MTB	
	N	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AHL	5	-3.1%	13.8	2973	4453	0.8	0.3	1.0	0.7
BIFS	67	7.9%	38.6	6237	13758	3.2	3.2	4.3	5.2
BLS	143	-70.6%	82.8	1342	6916	0.7	1.0	5.2	4.5
BS	127	-8.4%	76.8	16017	49653	3.3	8.2	6.3	11.2
CPRP	297	-40.3%	109.9	5740	16476	1.7	2.4	6.0	9.1
Com	72	-4.7%	34.3	12255	37919	1.8	2.5	3.4	3.0
CH	25	-5.8%	111.4	20954	43465	5.0	9.8	8.6	11.8
CS	85	-21.2%	95.5	13909	51546	2.5	6.0	8.4	10.4
Con	44	8.1%	14.0	6433	9619	1.5	1.0	2.1	2.0
FTM	57	14.0%	30.4	19536	43957	1.9	2.3	5.0	6.3
IEEM	449	-16.0%	87.5	9066	21867	1.9	5.2	8.4	15.8
LSCG	9	21.9%	27.9	17595	30251	5.3	9.1	4.0	2.4
MB	52	-27.5%	83.9	14460	35868	2.2	2.9	4.2	5.9
MMP	68	-5.5%	44.4	8109	10469	2.1	2.1	2.9	4.0
ME	79	-41.2%	71.8	4237	11317	1.7	1.7	1.6	2.1
MM	17	1.8%	35.8	4469	7770	3.8	6.1	4.0	4.9
PP	16	1.1%	137.9	8506	7602	5.1	7.7	11.4	38.4
PS	163	-2.8%	36.3	2359	11178	2.4	4.0	2.9	7.7
PAEHSS	53	-1.2%	123.8	19384	33570	4.6	11.8	7.0	13.7
Ret	106	17.3%	117.4	82420	268038	6.5	21.6	8.0	15.3
TCM	19	0.1%	31.1	14480	22049	1.9	1.9	3.4	4.3
TM	66	-7.6%	53.7	26815	46753	2.6	2.8	4.1	5.0
TFS	92	-10.8%	92.2	19712	63428	4.1	11.3	4.4	19.2
TPL	80	-36.2%	103.5	23529	56838	4.7	6.8	5.6	11.8
U	69	-2.8%	77.2	5846	6687	2.7	1.9	3.1	6.7
WMT	10	-16.7%	48.8	11708	16765	2.4	1.3	3.5	2.4
Whole	73	0.7%	47.4	14265	33996	3.2	4.7	3.9	5.8
WFPM	45	35.9%	114.5	10818	12745	3.5	7.3	6.7	15.9
Average		-15.7	86.5	13553	65729	2.6	6.9	5.7	11.5

Additionally, the firm-specific variables are averaged for the sectors in table 13. However, when we look at the sectors which were significantly impacted during the event periods, there is not a clear pattern recognized within the variable ROE, SIZE, D/E ratio and MTB ratio. So, these variables do not appear to have had a significant influence on the sectoral returns.

To summarize, all the four variables have a significant effect on the CARs during COVID-19, so these can be labelled as explanatory variables. This is in line with the research of Xiong et al. (2020) for ROE, SIZE & D/E and with Al-Awadhi et al. (2020) for MTB. Nevertheless, since the explained variance of the model is so low, this only accounts for a very small part.

7. Conclusions

This study has researched the effect of COVID-19 on the sectors of the US stock market. This has been executed by taking the daily share prices of the firms on the NYSE and NASDAQ and link these firms to the 28 BvD sectors with help of the unique Ticker Symbol of the stocks. For this study, four different event windows have been analysed with each 3 different event windows. After that, a post-event analysis has been conducted and a regression analysis as performed to control for third variables. The aim for this study is to provide investors with a better understanding of how different sectors respond during the COVID-19 pandemic. By learning from past pandemics, investors can better assess investment opportunities during future pandemics.

This research contributes to the current literature, first, since there was limited research available regarding the sectoral stock return during COVID-19 in the United States. Second, most event studies conducted on the effect of COVID-19 on the US stock market, have only applied 1 event date, whereas this study has analysed four different event dates, to compare in what phase of COVID-19, the stock market was impacted the most and when not. Finally, this study added a post-event analysis, which has not been executed in current literature regarding COVID-19 yet.

Then the conclusions of the results. First, for events 1-3 (January 21st, February 3rd and March 11th), the stock market experienced an average negative significant abnormal returns. This is in line with hypothesis. Additionally, the market during these events did not immediately responded to the event information, there was a delay in the abnormal stock price changes. So, this would reject the efficient market hypothesis. For the fourth event, March 23, 2020 however, the market did responded within the event window of [-3,3]. The investors responded very positive to the event: the pledge of the federal reserve. Nevertheless, nothing has changed about the seriousness of the COVID-19 virus, so it is more likely that the Behavioural Finance theory is applicable because of the investor sentiment and trust.

Second, the second hypothesis, about the sectoral returns. The individual sectors responded did not completely responded as predicted in hypothesis two. First, the sectors Manufacturing, the Public Administration, Education and Health Social Services and the Biotechnology and Life Sciences have not experienced significant positive abnormal returns during the first three events. Instead, the sectors Communications, Construction and Utilities experienced positive significant abnormal returns during the first event. Second, the sectors Banking, Insurance, & Financial Services, Business Services, Metals & Metal Products, Mining & Extraction, Transport, Freight & Storage, Textiles & Clothing Manufacturing, and Wholesale experienced negative abnormal returns during all event dates and event windows. In addition to that, the sectors Travel, Personal & Leisure and Property Services have not experienced significant negative abnormal returns during all three events and all event windows, however, these two sectors have been impacted the hardest. So, this is not entirely in line with the predictions of hypothesis two, the sectors BIFS, BS and TFS are consistent with the hypothesis, whereas the sector Utilities only experienced significant negative returns in event 3. The other sectors have not been outlined in the hypothesis.

Additionally, for the post-event analysis, the majority of the sectors do experience long term significant negative abnormal returns. Only the sector Property Services experienced long term significant negative abnormal returns, until 160 days after event 3, March 11, 2020. Moreover, the results of the regression emerge that the variables SIZE and ROE and MTB do positively influence the CARs during COVID-19, whereas the variable D/E negatively influences the CARS during COVID-19. Nevertheless, the explained variance was very low, so this only influences a very small aspect of the CARs. There appears to be no pattern between the sectoral average of these four variables and the CARs.

Then, the limitations. First of all, this research has been executed by equally averaging the share price returns of all companies within each sector. This method however, does not consider the size of a company for instance. For future research, this could be included by researching predefined sectoral indexes, which already considered the size difference. Another limitation, are the sectors. Since only the BvD sectors were available to me via Orbis, I was forced to implement these sectors within the study. However, no other study has used the exact same sectors and therefore it is difficult to compare. Moreover, the estimation period that was used was 252 trading days, which is a common estimation period, however, the period before the COVID-19 virus started, was a period with relatively high share prices, so maybe the estimation period could have influenced the results. To solve this, a future research could include a longer estimation period. Another important recommendation for future research, is the fourth event period: March 23, 2020. I have found no research regarding this event date, even though this is the time that the share prices started to raise again. As mentioned in the research, this could be caused by the Behavioural Finance theory and the trust and investor sentiment. However, this could be researched much more into depth. For instance, a research that compares the investor sentiment, trust or fear from the COVID-19 period before March 23, 2020 (the announcement of the federal reserve), and after. Another interesting research subject, is the amount of media coverage on COVID-19 and how this possibly has affected the share prices.

Finally, practical recommendations for investors should be provided. Stock prices during COVID-19 and other pandemics, experienced a large decreased, however, relatively quick, the share prices recovered as well. So, one implication for investors could be: Don’t sell your shares, because the market will recover. Additionally, one could advise to invest more when the share prices have decreased and reach the ultimate low, however, no one knows when the ultimate low point will be so this is a more abstract recommendation. Besides this, this study focussed on the specific sectors and how these responded. One sectors which experienced a very strong significant negative abnormal return, was the Travel, Personal & Leisure sector. This sector was also negatively impacted during other pandemics. So, in case of a future pandemic, investors could specifically sell their travel and leisure related shares to prevent a large decrease in their portfolio. Finally, the specifically for COVID-19, the Transport, Freight and Storage sector experienced many negative significant abnormal returns. Since this was likely related to the worldwide lock downs and restrictions, investors could remember for future pandemics or lock downs, that their transport related shares will likely be impacted, and therefore could make the choice to sell these shares.

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Appendix A

Table 1
Frequency distribution of BvD sectors

BvD Sectors	Abbreviations	Frequency	Percent	Cumulative Percent
Agriculture, Horticulture & Livestock	AHL	8	0.2	0.2
Banking, Insurance & Financial Services	BIFS	935	22.7	22.9
Biotechnology and Life Sciences	BLS	172	4.2	27.1
Business Services	BS	501	12.2	39.3
Chemicals, Petroleum, Rubber & Plastic	CPRP	358	8.7	48
Communications	Com	92	2.2	50.2
Computer Hardware	CH	27	0.7	50.9
Computer Software	CS	105	2.6	53.5
Construction	Con	49	1.2	54.6
Food & Tobacco Manufacturing	FTM	64	1.6	56.2
Industrial, Electric & Electronic Machinery	IEEM	529	12.9	69.1
Leather, Stone, Clay & Glass products	LSCG	12	0.3	69.4
Media & Broadcasting	MB	73	1.8	71.1
Metals & Metal Products	MMP	77	1.9	73
Mining & Extraction	ME	98	2.4	75.4
Miscellaneous Manufacturing	MM	17	0.4	75.8
Printing & Publishing	PP	19	0.5	76.3
Property Services	PS	202	4.9	81.2
Public Administration, Education, Health Social Services	PAEHSS	67	1.6	82.8
Retail	Ret	133	3.2	86
Textiles & Clothing Manufacturing	TCM	27	0.7	86.7
Transport Manufacturing	TM	77	1.9	88.6
Transport, Freight & Storage	TFS	129	3.1	91.7
Travel, Personal & Leisure	TPL	117	2.8	94.6
Utilities	U	77	1.9	96.4
Waste Management & Treatment	WMT	11	0.3	96.7
Wholesale	Whole	87	2.1	98.8
Wood, Furniture & Paper Manufacturing	WFPM	49	1.2	100
Total		4112	100	100

Table 2

AR sectors on event date [0,0]

BvD 28 sectors		Event 1		Event 2		Event 3		Event 4	
	Df	*Mean*	*t-test*	*Mean*	*t-test*	*Mean*	*t-test*	*Mean*	*t-test*
AHL	7	0.20%	0.52	0.59%	0.39	-0.91%	-0.51	-1.02%	-1.87
BIFS	934	-0.16%	-3.78***	-0.08%	-1.46	-2.05%	-19.99***	-3.42%	-15.49***
BLS	171	0.88%	0.66	0.10%	0.26	-0.47%	-0.91	3.86%	6.82***
BS	500	-0.43%	-4.78***	0.09%	1.03	-1.10%	-6.34***	-1.21%	-3.71***
CPRP	357	0.22%	0.68	0.26%	0.90	0.16%	0.47	1.96%	5.13***
Com	91	-0.07%	-0.23	-0.88%	-2.20**	0.10%	0.17	2.21%	3.33***
CH	26	-0.05%	-0.11	0.17%	0.47	-0.62%	-0.73	4.49%	2.71**
CS	104	0.01%	0.05	0.09%	0.45	-0.09%	-0.17	2.73%	3.82***
Con	48	1.09%	2.93***	-0.11%	-0.32	-2.59%	-3.27***	-2.28%	-1.87*
FTM	63	0.34%	1.03	0.06%	0.24	-0.97%	-2.00**	-0.25%	-0.30
IEEM	528	0.09%	0.58	-0.39%	-2.64***	0.72%	1.69*	2.72%	8.70***
LSCG	11	-0.67%	-1.26	0.35%	0.71	-0.27%	-0.28	-0.59%	-0.54
MB	72	-0.46%	-1.38	0.11%	0.35	0.07%	0.13	2.23%	2.53**
MMP	76	-1.43%	-6.48***	0.13%	0.43	0.80%	1.78*	2.19%	3.14***
ME	97	-2.65%	-7.68***	-2.18%	-5.52***	-1.93%	-2.52**	-0.90%	-1.05
MM	16	0.46%	1.00	-1.64%	-1.96*	-1.54%	-1.01	1.62%	1.15
PP	18	-0.89%	-2.74**	-0.13%	-0.47	-1.76%	-2.16**	-1.97%	-0.98
PS	201	0.76%	8.38***	0.12%	1.28	-4.74%	-18.34***	-2.35%	-3.91***
PAEHSS	66	0.20%	0.39	1.14%	1.35	-1.26%	-1.29	1.90%	1.87*
Ret	132	-0.44%	-2.02**	0.14%	0.72	-1.66%	-4.16***	1.14%	1.52
TCM	26	-0.18%	-0.30	-0.94%	-1.88*	0.03%	0.02	1.53%	0.77
TM	76	-0.71%	-2.56**	0.28%	0.80	0.69%	1.24	2.24%	2.62**
TFS	128	-2.10%	-9.71***	-0.64%	-2.43**	-0.47%	-1.04	1.65%	1.72*
TPL	116	-1.21%	-5.69***	-0.28%	-1.55	-4.91%	-9.88***	4.45%	4.36***
U	76	0.19%	0.98	0.51%	2.17**	-3.44%	-7.35***	-3.68%	-5.61***
WMT	10	0.10%	0.11	-1.02%	-1.27	-0.66%	-0.39	-2.40%	-1.01
Whole	86	-0.49%	-1.63	-0.28%	-0.99	0.07%	0.12	-0.44%	-0.47
WFPM	48	-0.06%	-0.18	-0.30%	-0.98	-0.91%	-2.19**	-0.34%	-0.35
Average		-0.3%	-1.19	-0.2%	-0.43	-1.1%	-2.82	0.6%	0.47

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Appendix B

Table 1

Tests of Normality January 21, 2020

		Shapiro-Wilk [10,10]		Shapiro-Wilk [-5,5]		Shapiro-Wilk [-3,3]	
	df	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.
AHL	8	0.867	0.142	0.955	0.764	0.881	0.194
CH	27	0.943	0.143	0.764	0.000*	0.696	0.000*
LSCG	12	0.866	0.058	0.961	0.802	0.926	0.338
MM	17	0.667	0.000*	0.936	0.273	0.844	0.009*
PP	19	0.730	0.000*	0.912	0.079	0.971	0.790
TCM	27	0.907	0.020*	0.822	0.000*	0.966	0.498
WMT	11	0.837	0.029*	0.689	0.000*	0.663	0.000*

** Represents a 95% confidence interval*

Table 2

Tests of Normality February 3, 2020

		Shapiro-Wilk [10,10]		Shapiro-Wilk [-5,5]		Shapiro-Wilk [-3,3]	
	df	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.
AHL	8	0.936	0.576	0.950	0.715	0.862	0.126
CH	27	0.923	0.048*	0.967	0.515	0.889	0.008*
LSCG	12	0.650	0.000*	0.894	0.133	0.764	0.004*
MM	17	0.435	0.000*	0.672	0.000*	0.583	0.000*
PP	19	0.978	0.912	0.980	0.945	0.857	0.009*
TCM	27	0.943	0.141	0.923	0.047*	0.945	0.162
WMT	11	0.968	0.869	0.901	0.193	0.884	0.116

** Represents a 95% confidence interval*

Table 3

Tests of Normality March 11, 2020

		Shapiro-Wilk [10,10]		Shapiro-Wilk [-5,5]		Shapiro-Wilk [-3,3]	
	df	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.
AHL	8	0.976	0.943	0.953	0.746	0.909	0.348
CH	27	0.943	0.142	0.863	0.002*	0.956	0.298
LSCG	12	0.928	0.363	0.952	0.668	0.954	0.697
MM	17	0.879	0.031*	0.950	0.449	0.982	0.975
PP	19	0.923	0.127	0.949	0.385	0.942	0.288
TCM	27	0.960	0.366	0.974	0.709	0.933	0.084
WMT	11	0.767	0.003*	0.925	0.367	0.836	0.028*

** Represents a 95% confidence interval*

Table 4

Tests of Normality March 23, 2020

		Shapiro-Wilk [10,10]		Shapiro-Wilk [-5,5]		Shapiro-Wilk [-3,3]	
	df	Statistic	Sig.	Statistic	Sig.	Statistic	Sig.
AHL	8	0.955	0.765	0.948	0.694	0.850	0.095
CH	27	0.902	0.015*	0.817	0.000*	0.827	0.000*
LSCG	12	0.950	0.632	0.903	0.172	0.976	0.963
MM	17	0.978	0.939	0.904	0.079	0.790	0.001*
PP	19	0.747	0.000*	0.879	0.021*	0.869	0.014*
TCM	27	0.969	0.577	0.914	0.029*	0.967	0.536
WMT	11	0.855	0.050	0.720	0.001*	0.916	0.283

** Represents a 95% confidence interval*

Appendix C

Table 1

CAR of the sectors of event date 1: January 21,2020

BvD 28 sectors	[-3,3]		[-5,5]		[-10,10	
	t-test	*Wilcoxon*	t-test	*Wilcoxon*	t-test	*Wilcoxon*
CH	0.48	-0.72	0.53	-0.63	-1.13	-1.59
LSCG	-1.27	-1.10	-0.92	-0.94	0.66	-0.08
MM	-0.64	-1.30	0.36	-0.59	0.30	-0.69
PP	-1.67	-1.69*	-0.97	-0.77	-2.41*	-2.58***
TCM	-2.32*	-2.33**	-2.00*	-1.99**	-4.71***	-3.90***
WMT	-0.55	-0.62	-0.26	-0.8	-1.88*	-1.70*

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 2

CAR of the sectors of event date 2: February 3, 2020

BvD 28 sectors	[-3,3]		[-5,5]		[-10,10	
	t-test	*Wilcoxon*	t-test	*Wilcoxon*	t-test	*Wilcoxon*
CH	-3.77***	-3.58***	-4.19***	-3.41***	-2.43*	-2.69***
LSCG	0.74	-0.08	0.18	-0.39	0.10	-1.10
MM	-2.25*	-2.91***	-2.65*	-3.15***	0.17	-2.68***
PP	-0.04	-0.72	-1.28	-1.41	-2.00*	-1.97**
TCM	-4.16***	-3.29***	-4.91***	-3.84***	-4.17***	-3.60***
WMT	-1.62	-1.78*	-1.37	-1.42	-1.78	-1.51

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 3

CAR of the sectors of event date 3: March 11, 2020

BvD 28 sectors	[-3,3]		[-5,5]		[-10,10	
	t-test	*Wilcoxon*	t-test	*Wilcoxon*	t-test	*Wilcoxon*
CH	-2.14*	-1.87*	-2.53*	-2.14**	-0.80	-0.36
LSCG	-2.48*	-2.04**	-3.50***	-2.59***	-3.09*	-2.35
MM	-2.13*	-1.87*	-2.78*	-2.44**	-1.66	-1.11
PP	0.18	-0.04	-2.66*	-2.29**	-2.83*	-2.37
TCM	-5.93***	-4.23***	-5.42***	-4.01***	-3.66***	-3.08
WMT	-2.00*	-2.05**	-3.62***	-2.40**	-1.00	-1.42

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 4

CAR of the sectors of event date 4: March 23, 2020

BvD 28 sectors	[-3,3]		[-5,5]		[-10,10	
	t-test	*Wilcoxon*	t-test	*Wilcoxon*	t-test	*Wilcoxon*
CH	2.53*	-2.07**	0.92	-1.61	-1.21	-0.55
LSCG	1.51	-1.33	-0.81	-0.16	-3.29***	-2.51***
MM	1.32	-0.78	1.35	-1.07	-1.67	-1.54
PP	-1.08	-0.32	-2.84*	-2.54**	-2.74*	-2.86***
TCM	2.50*	-0.96	-0.98	-2.07**	-3.88***	-3.58***
WMT	2.45*	-2.13**	0.56	-0.18	-1.76	-1.6

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Appendix D

Table 1

Post-event analysis of the sectors of event date March 11, 2020

BvD 28 sectors		[0,20]			[0,40]			[0,60]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	-5.9%	11.7%	-1.43	-6.8%	20.0%	-0.96	4.4%	15.6%	0.80
BIFS	934	-8.1%	12.5%	-19.86***	-6.1%	16.5%	-11.34***	1.0%	18.0%	1.64
BLS	171	0.6%	34.4%	0.23	17.8%	47.8%	4.89***	19.2%	66.5%	3.79***
BS	500	-7.4%	16.5%	-10.03***	-6.4%	20.1%	-7.14***	5.5%	27.3%	4.51***
CPRP	357	1.7%	29.2%	1.12	13.7%	51.3%	5.05***	15.3%	72.3%	4.00***
Com	91	4.5%	19.9%	2.19**	11.4%	32.8%	3.34***	18.3%	43.6%	4.03***
CH	26	-5.0%	24.7%	-1.05	4.8%	24.2%	1.04	8.6%	31.5%	1.43
CS	104	-1.5%	15.7%	-0.98	12.9%	33.0%	4.00***	19.3%	50.4%	3.92***
Con	48	-7.1%	-238.5%	0.02	-2.1%	19.3%	-0.76	17.0%	23.4%	5.10***
FTM	63	5.2%	37.5%	1.11	6.1%	32.6%	1.50	7.9%	40.1%	1.57
IEEM	528	1.3%	28.8%	1.06	9.2%	38.2%	5.52***	13.6%	45.6%	6.84***
LSCG	11	-3.0%	19.9%	-0.52	-0.7%	16.4%	-0.15	19.3%	23.7%	2.82**
MB	72	-0.9%	37.9%	-0.20	11.9%	57.1%	1.78*	25.6%	78.0%	2.81***
MMP	76	-0.5%	43.1%	-0.11	-1.9%	40.9%	-0.42	13.3%	41.7%	2.81***
ME	97	6.8%	27.7%	2.42**	86.0%	558.7%	1.52	110.8%	573.4%	1.91*
MM	16	-4.4%	20.5%	-0.89	15.4%	44.3%	1.43	33.3%	51.3%	2.68**
PP	18	-14.3%	28.8%	-2.17**	-9.1%	24.7%	-1.61	13.3%	25.1%	2.32**
PS	201	-16.0%	21.8%	-10.43***	-15.7%	22.7%	-9.84***	2.4%	23.4%	1.46
PAEHSS	66	-6.6%	26.1%	-2.08**	-1.4%	30.1%	-0.39	3.1%	29.4%	0.88
Ret	132	-6.8%	23.2%	-3.38***	3.7%	32.7%	1.31	22.4%	35.9%	7.19***
TCM	26	-12.1%	22.4%	-2.80***	-6.2%	29.5%	-1.09	13.3%	37.1%	1.87*
TM	76	-7.9%	27.2%	-2.56**	-1.5%	35.7%	-0.38	19.5%	38.1%	4.50***
TFS	128	-4.0%	31.7%	-1.42	2.9%	38.0%	0.87	17.3%	46.9%	4.18***
TPL	116	-11.8%	21.9%	-5.84***	-1.2%	28.7%	-0.47	22.5%	40.3%	6.03***
U	76	-1.6%	15.0%	-0.91	-4.4%	19.7%	-1.96*	1.9%	20.6%	0.83
WMT	10	0.2%	25.1%	0.03	-7.6%	19.1%	-1.32	3.4%	26.1%	0.43
Whole	86	-1.6%	19.3%	-0.76	6.7%	26.2%	2.39**	20.4%	32.6%	5.85***
WFPM	48	-9.7%	13.8%	-4.90***	-3.0%	20.0%	-1.06	11.0%	21.8%	3.54***
Average		-4.1%	14.9%	-2.29	4.6%	49.3%	-0.15	17.3%	56.4%	3.20

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 2

Post-event analysis of the sectors of event date March 11, 2020

BvD 28 sectors		[0,80]			[0,100]			[0,120]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	15.3%	28.4%	1.52	7.9%	33.3%	0.67	9.8%	38.3%	0.72
BIFS	934	-1.2%	21.2%	-1.71*	-0.6%	22.4%	-0.76	-1.3%	29.1%	-1.33
BLS	171	20.2%	78.9%	3.36***	14.4%	92.2%	2.05**	9.0%	117.8%	1.00
BS	500	-1.5%	32.2%	-1.06	-3.2%	34.9%	-2.08**	-4.8%	35.6%	-3.04***
CPRP	357	17.8%	92.7%	3.63***	20.2%	119.3%	3.20***	13.9%	161.6%	1.62
Com	91	22.4%	52.0%	4.14***	27.7%	56.7%	4.69***	19.9%	55.4%	3.45***
CH	26	8.1%	39.6%	1.06	8.8%	45.6%	1.01	10.5%	53.9%	1.02
CS	104	32.5%	96.9%	3.44***	36.0%	100.6%	3.67***	30.8%	98.2%	3.21***
Con	48	14.2%	26.3%	3.78***	20.6%	28.5%	5.06***	22.2%	33.0%	4.70***
FTM	63	6.9%	44.5%	1.24	9.3%	49.0%	1.53	9.4%	47.1%	1.61
IEEM	528	16.2%	58.4%	6.39***	22.1%	73.5%	6.92***	15.3%	76.9%	4.58***
LSCG	11	23.7%	32.1%	2.56**	23.7%	32.2%	2.55**	14.7%	28.8%	1.76
MB	72	35.2%	90.8%	3.31***	40.0%	95.6%	3.57***	37.0%	91.4%	3.46***
MMP	76	10.1%	48.1%	1.84*	12.5%	53.0%	2.06**	10.1%	51.7%	1.71*
ME	97	100.6%	570.0%	1.75*	102.6%	572.7%	1.77*	109.1%	577.5%	1.87*
MM	16	41.2%	71.4%	2.38**	43.6%	75.4%	2.39**	42.7%	87.6%	2.01*
PP	18	2.3%	28.1%	0.36	7.5%	38.1%	0.86	7.2%	40.5%	0.77
PS	201	-5.7%	25.7%	-3.14***	-9.6%	30.7%	-4.44***	-9.5%	32.4%	-4.18***
PAEHSS	66	1.8%	37.9%	0.39	7.4%	45.0%	1.35	6.3%	52.5%	0.99
Ret	132	24.3%	48.6%	5.77***	30.2%	64.1%	5.44***	33.5%	68.0%	5.67***
TCM	26	12.7%	56.2%	1.18	11.6%	60.4%	1.00	9.0%	57.1%	0.82
TM	76	23.8%	49.1%	4.26***	24.4%	54.1%	3.97***	22.0%	54.4%	3.55***
TFS	128	8.0%	52.1%	1.74*	6.5%	59.9%	1.23	5.0%	66.6%	0.85
TPL	116	10.7%	40.0%	2.88***	10.5%	49.8%	2.28**	21.9%	50.5%	4.68***
U	76	-2.0%	30.1%	-0.60	-0.9%	35.7%	-0.23	-0.9%	46.0%	-0.18
WMT	10	4.6%	39.2%	0.39	3.6%	40.3%	0.29	-1.6%	39.0%	-0.14
Whole	86	15.6%	33.6%	4.32***	21.6%	46.7%	4.32***	20.0%	46.0%	4.05***
WFPM	48	10.8%	34.7%	2.18**	15.5%	42.8%	2.53**	13.6%	43.0%	2.21**
Average		16.7%	66.4%	2.05	18.4%	73.3%	2.03	16.9%	77.9%	1.69

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 3

Post-event analysis of the sectors of event date March 11, 2020

BvD 28 sectors		[0,140]			[0,160]			[0,180]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	24.8%	55.2%	1.27	31.7%	64.9%	1.38	35.4%	66.9%	1.50
BIFS	934	-0.9%	46.7%	-0.58	0.6%	51.6%	0.37	8.2%	60.8%	4.14***
BLS	171	12.2%	129.8%	1.23	11.0%	142.5%	1.01	11.1%	160.9%	0.91
BS	500	-5.2%	36.3%	-3.21***	2.2%	39.5%	1.26	15.8%	40.3%	8.80***
CPRP	357	16.2%	175.5%	1.74*	16.1%	191.5%	1.59	21.2%	213.5%	1.88*
Com	91	24.4%	69.0%	3.39***	28.0%	73.1%	3.67***	35.7%	80.0%	4.29***
CH	26	11.9%	56.6%	1.09	10.5%	58.0%	0.94	17.7%	58.9%	1.56
CS	104	36.9%	104.4%	3.62***	40.5%	109.4%	3.79***	45.3%	114.2%	4.07***
Con	48	28.6%	38.0%	5.26***	28.9%	41.7%	4.85***	38.3%	47.1%	5.69***
FTM	63	8.3%	51.5%	1.30	12.0%	53.4%	1.80*	16.4%	57.3%	2.30**
IEEM	528	18.9%	85.0%	5.10***	21.4%	94.2%	5.22***	33.4%	156.2%	4.92***
LSCG	11	18.5%	31.6%	2.03*	28.8%	31.7%	3.14***	34.6%	40.7%	2.95**
MB	72	38.1%	95.0%	3.42***	38.6%	96.2%	3.43***	64.8%	120.8%	4.59***
MMP	76	14.7%	55.7%	2.31**	21.0%	62.2%	2.96***	35.3%	65.4%	4.74***
ME	97	105.2%	574.7%	1.81*	106.7%	576.5%	1.83*	133.1%	579.9%	2.27**
MM	16	50.8%	97.4%	2.15**	61.1%	107.4%	2.35**	65.8%	102.4%	2.65**
PP	18	8.3%	43.7%	0.83	6.3%	46.7%	0.59	24.3%	49.6%	2.13**
PS	201	-12.0%	32.6%	-5.24***	-13.4%	37.5%	-5.09***	11.4%	98.7%	1.64
PAEHSS	66	4.1%	63.2%	0.54	6.4%	70.9%	0.74	12.6%	74.7%	1.38
Ret	132	38.0%	72.2%	6.08***	46.1%	77.6%	6.85***	59.2%	90.8%	7.52***
TCM	26	14.6%	56.5%	1.35	35.2%	74.1%	2.47**	54.1%	80.2%	3.51***
TM	76	25.6%	57.8%	3.89***	30.2%	61.1%	4.34***	51.4%	70.3%	6.41***
TFS	128	4.8%	71.8%	0.75	5.3%	80.0%	0.75	28.7%	157.1%	2.08**
TPL	116	24.9%	53.3%	5.05***	26.5%	52.4%	5.48***	42.9%	51.5%	9.00***
U	76	-2.7%	48.7%	-0.49	4.7%	54.8%	0.75	10.3%	67.4%	1.35
WMT	10	-1.9%	49.3%	-0.13	-5.8%	54.2%	-0.36	7.4%	53.7%	0.46
Whole	86	20.6%	50.4%	3.81***	24.7%	54.1%	4.26***	34.2%	52.3%	6.10***
WFPM	48	17.2%	48.4%	2.49**	23.5%	68.8%	2.39**	28.6%	70.5%	2.84***
Average		19.5%	84.0%	1.82	23.2%	90.2%	2.24	34.9%	102.9%	3.63

*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

Table 4

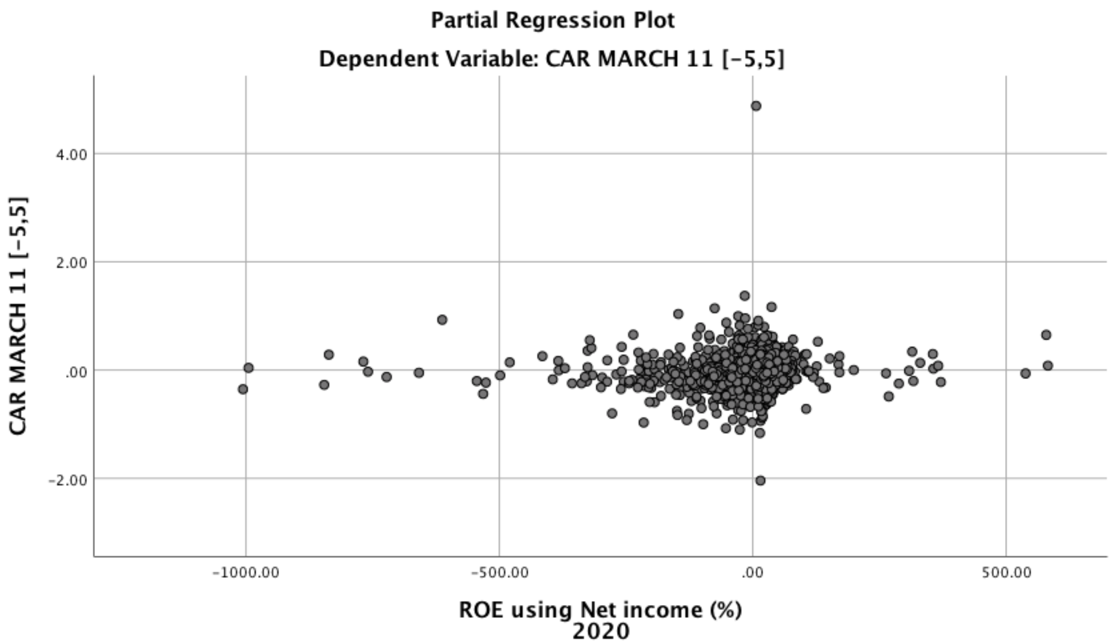
Post-event analysis of the sectors of event date March 11, 2020

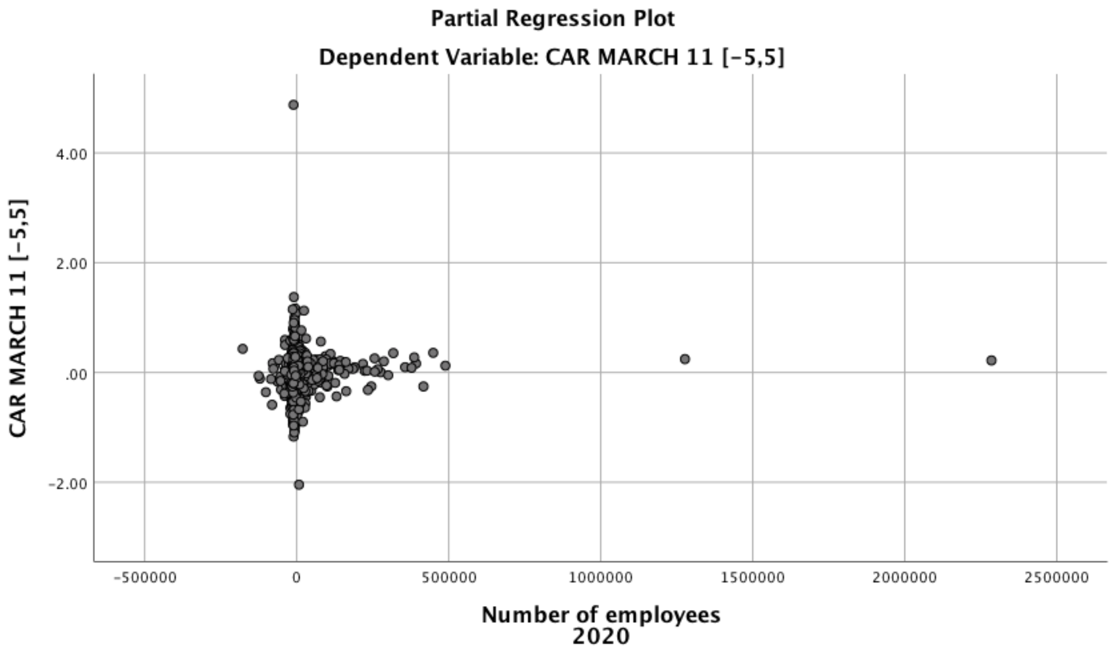
BvD 28 sectors		[0,200]			[0,220]			[0,240]		
	dF	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*	*Mean*	*SD*	*t-test*
AHL	7	43.6%	75.6%	1.63	48.5%	82.4%	1.66	50.5%	90.0%	1.59
BIFS	934	10.0%	60.2%	5.08***	11.8%	62.7%	5.77***	14.8%	64.7%	7.01***
BLS	171	26.3%	177.8%	1.94*	37.2%	198.2%	2.46**	40.3%	209.5%	2.53**
BS	500	17.3%	44.0%	8.79***	23.6%	62.9%	8.41***	33.6%	65.7%	11.46***
CPRP	357	42.1%	256.1%	3.11***	51.0%	274.4%	3.52***	57.9%	290.5%	3.77***
Com	91	44.9%	86.4%	4.99***	60.0%	106.7%	5.40***	74.6%	142.2%	5.03***
CH	26	30.7%	66.8%	2.39**	38.0%	67.4%	2.93***	49.5%	74.3%	3.46***
CS	104	54.9%	118.3%	4.76***	63.1%	131.8%	4.90***	71.3%	140.4%	5.20***
Con	48	39.9%	51.9%	5.38***	46.8%	56.5%	5.80***	52.9%	59.1%	6.27***
FTM	63	15.1%	59.8%	2.02**	21.3%	67.8%	2.52**	24.6%	68.4%	2.88***
IEEM	528	53.9%	220.0%	5.64***	65.6%	230.4%	6.55***	71.1%	236.0%	6.93***
LSCG	11	33.8%	41.9%	2.79**	54.7%	81.3%	2.33**	85.9%	124.9%	2.38**
MB	72	74.3%	137.2%	4.63***	91.5%	150.5%	5.20***	107.1%	158.9%	5.76***
MMP	76	39.8%	75.7%	4.61***	47.4%	93.0%	4.47***	58.0%	93.0%	5.47***
ME	97	143.3%	580.8%	2.44**	153.4%	579.8%	2.62**	181.8%	584.8%	3.08***
MM	16	73.0%	106.0%	2.84**	77.5%	113.1%	2.83**	83.1%	113.1%	3.03***
PP	18	27.9%	50.8%	2.39**	38.6%	53.9%	3.12***	52.9%	61.6%	3.75***
PS	201	18.6%	121.6%	2.17**	21.0%	124.9%	2.39**	27.6%	125.8%	3.12***
PAEHSS	66	51.0%	221.5%	1.89	56.1%	232.5%	1.98	58.1%	239.2%	1.99
Ret	132	62.6%	96.3%	7.50***	78.5%	107.7%	8.41***	85.2%	118.4%	8.30***
TCM	26	61.9%	93.1%	3.46***	70.1%	111.6%	3.26***	94.3%	156.9%	3.12***
TM	76	54.6%	72.9%	6.58***	58.8%	82.5%	6.25***	63.6%	83.1%	6.71***
TFS	128	30.3%	164.5%	2.09**	37.8%	173.7%	2.47**	53.6%	182.3%	3.34***
TPL	116	46.8%	54.3%	9.32***	52.4%	60.6%	9.35***	67.9%	70.3%	10.44***
U	76	8.6%	75.0%	1.01	12.2%	86.2%	1.25	10.4%	84.0%	1.08
WMT	10	3.8%	59.5%	0.21	20.0%	73.4%	0.90	23.5%	76.9%	1.01
Whole	86	35.1%	55.2%	5.93***	39.2%	61.2%	5.98***	46.1%	63.8%	6.74***
WFPM	48	32.1%	80.7%	2.78***	34.7%	85.2%	2.86***	40.6%	87.3%	3.25***
Average		42.0%	118.0%	3.87	50.4%	129.0%	4.13	60.0%	138.0%	4.60

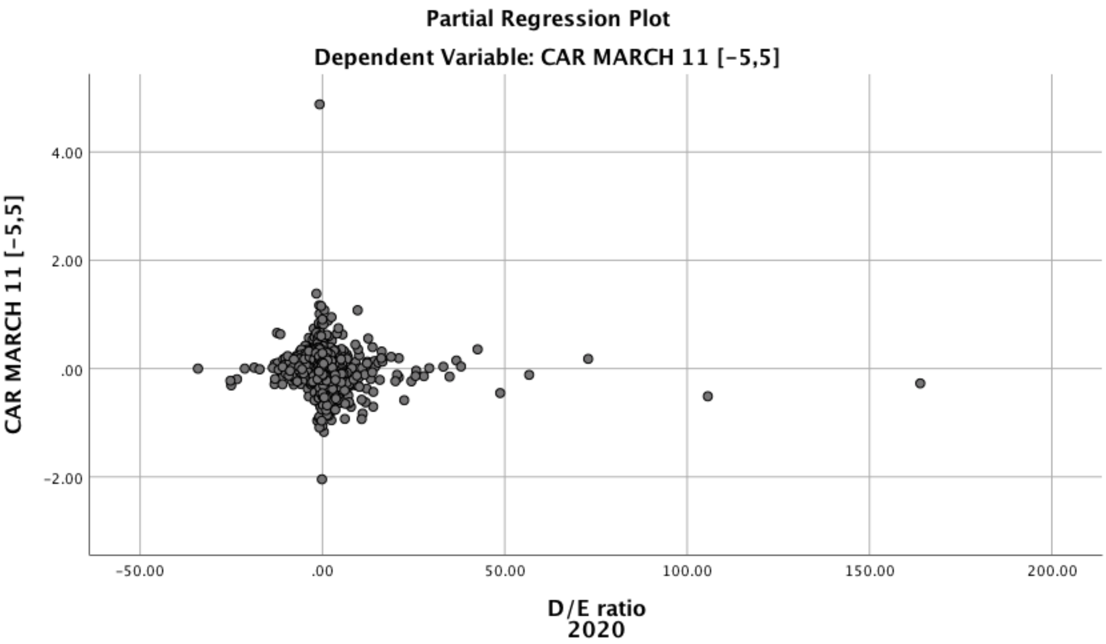
*Note: *,**,*** represent the statistical significance of the t-test and at 10%, 5%, and 1% respectively*

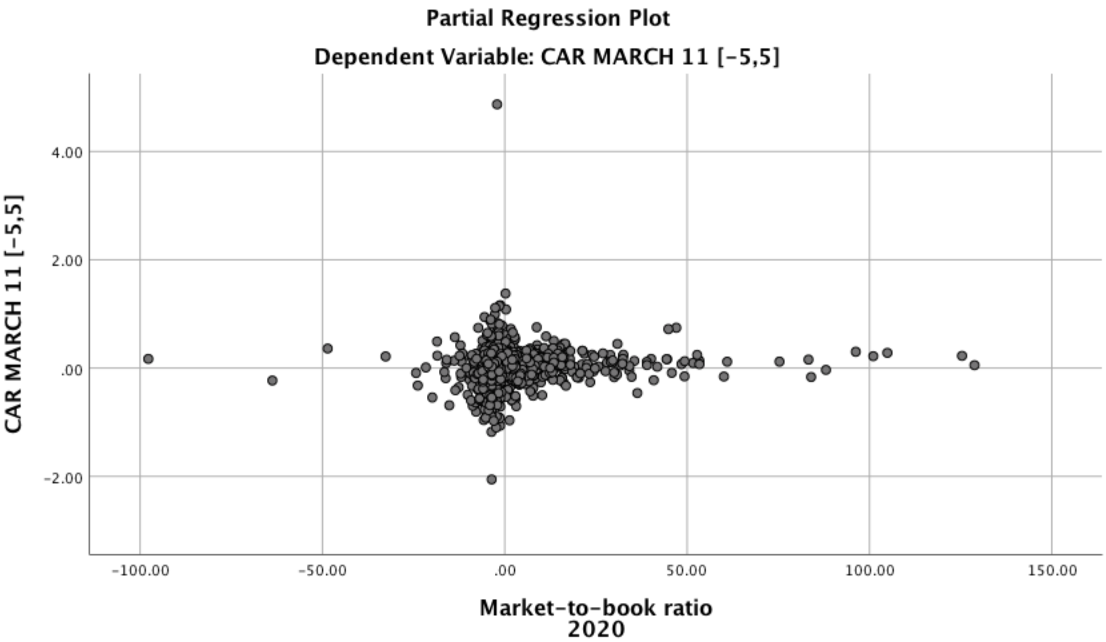
Appendix E

** All event windows have been tested, however, since the results are very similar, only the results of event window [-5,5] are presented:*



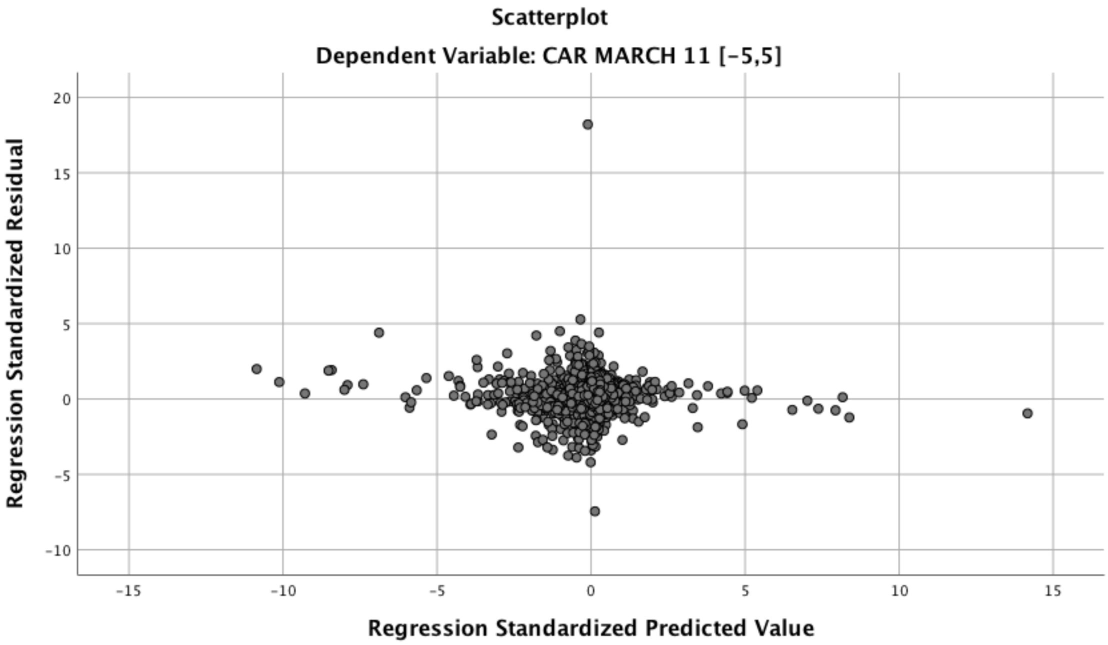



Partial Regression Plot
Dependent Variable: CAR MARCH 11 [-5,5]
CAR MARCH 11 [-5,5]
4.00
2.00
.00
-2.00
-50.00
.00
50.00
100.00
150.00
200.00
D/E ratio
2020


Partial Regression Plot
Dependent Variable: CAR MARCH 11 [-5,5]
CAR MARCH 11 [-5,5]
4.00
2.00
.00
-2.00
-100.00
-50.00
.00
50.00
100.00
150.00
Market-to-book ratio
2020

Appendix F

All event windows have been tested, however, since the results are very similar, only the results of event window [-5,5] are presented:



Appendix G

All event windows have been tested, however, since the results are very similar, only the results of event window [-5,5] are presented: