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Master Thesis

A Comparison of the Stock Price Reaction After a Large One-Day Price Movement Before and During the COVID-19 Pandemic

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Abstract

This paper examines the difference in the short-term reaction of stock returns in the U.S. stock market after a large one-day price movement before and during the COVID-19 pandemic. This has been done by investigating the cumulative abnormal returns of NYSE stocks after a large one-day price, for both rises and drops. Two periods are investigated, before the COVID-19 pandemic from November 2018 to October 2019 and during the COVID-19 pandemic from April 2020 to March 2021. The main conclusion of this paper is that only a difference in the short-term reaction of stock returns in the U.S. stock market after a large one-day price rise can be found when comparing the period before and during the COVID-19 pandemic.

Keywords: COVID-19 pandemic, event study, United States, New York Stock Exchange, abnormal return, reversal effect, overreaction hypothesis

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1 Introduction

The COVID-19 virus has turned the world upside down. Everything has been impacted. How we live and interact with each other, how we work and communicate, how we move around and travel. Every aspect of our lives has been affected.

Also for the capital markets, the COVID-19 virus made a big impact. Its outbreak triggered a freefall in share prices. After historically large and rapid declines across all sectors, when all news was bad and the downside seemed unlimited, the governments introduced enormous stimulus packages.[1] Stocks started to rise again, but the recovery was far from even, industries like aerospace, banking, insurance and oil and gas remained down significantly from their pre-pandemic peaks. While other industries, like technology and electric vehicles, were strongly gaining. At the end of September 2020, almost half the sectors had fully bounced back to their pre-pandemic levels. Early November, positive news about the results of vaccine trials caused even the worst-hit industries to partially regain their market losses. However, the spread between the best- and worst-performing sectors also grew from 27 percentage points in mid-March 2020 to 80 percentage points in mid-March 2021, the widest in recent history.[2]

Big price movements were not the only remarkable aspect about the developments in the capital markets. Trading by individuals accounted for a greater part of market activity than at any time during the past 10 years. On some days in 2020, about 25% of the market volume in the U.S. stock market was individual-investor activity. By contrast, this group made up just 10% of the market in 2019.[3] This share grew due to decreasing brokerage fees and simplified possibilities to actively manage a portfolio by smartphone. Moreover, the pandemic played a major role: a lot of people were sitting at home with little to do and were unable to spend their money on vacation or other activities. That Nick Maggiulli, chief operating officer of Ritholtz Wealth Management, proved that these retail investors have an impact on the market. He found strong correlations between stocks' popularity on

[1] McKinsey & Company. The $10 trillion rescue: How governments can deliver impact. Retrieved from https://www.mckinsey.com/industries/public-and-social-sector/our-insights/the-10-trillion-dollar-rescue-how-governments-can-deliver-impact

[2] McKinsey & Company. The impact of COVID-19 on capital market, one year in. Retrieved from https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/the-impact-of-covid-19-on-capital-markets-one-year-in

[3] Bloomberg. Citaldel Securities'Mecane Says Volatility Behind Rise in Retail Investing. Retrieved from https://www.bloomberg.com/news/videos/2020-07-09/citadel-s-mecane-says-volatility-behind-rise-in-retail-investing-video?sref=rcmlg3wG

Robinhood, a financial services company known for offering commission-free trades of stocks and ETFs via a mobile app, and their price.[4]

Critics say that retail investors do not have the knowledge, discipline or expertise to critically examine their investments. As a result, they undermine the financial markets' role in allocating resources efficiently; and through crowded trades, cause panic selling. These unsophisticated investors are said to be vulnerable to behavioural biases and may underestimate the power of the masses driving the market.

As the market structure has changed extensively in recent years, it's interesting to examine whether past theories still hold in today's market. The overreaction theory is typically a theory that has a big behavioural aspect, where people overweight recent information and underweight prior data and therefore overreact on certain unexpected or dramatic events. If retail investors are indeed vulnerable to behavioural biases, will the results of the overreaction phenomenon be larger in the current market?

This paper compares the short-term reaction of stock returns to large price movements in the current market with the market before the pandemic, to see if the behaviour of the market has changed since the pandemic. The research question is as follows:

"To what extent has the reaction of stock returns to large one-day price movements in the U.S. stock market in the short-run changed since the COVID-19 pandemic?"

This paper contributes to the existing literature because the structure of the U.S. stock market has changed since the COVID-19 pandemic and therefore it is important to see if the reaction of the stock returns following large price movements is still the same as before the pandemic. Plastun et al. (2021) found that before the Global Financial Crisis, a momentum strategy was a profitable strategy after large stock price movements but during and after the Global Financial Crisis the profitable strategy changed in a contrarian strategy. He claims that one of the possible reasons for the evolution of financial markets can be crisis periods. It is therefore interesting to see if the reaction of the stock returns following large price movements is still the same as before the pandemic. If this is not the case, it may be important to look at other investment strategies as well to check if those are still profitable. Furthermore, a lot of papers have studied only cumulative abnormal returns after a large one-day drop or large one-day rise. This paper will study both large one-day drops and rises. This is important whether to conclude if the results are in line with the Uncertain Information Hypothesis. Further, most

[4] Osipovich, A. (2020). Individuals reshape stock market. *Wall Street Journal*, Retrieved from https://www-proquest-com.eur.idm.oclc.org/newspapers/individuals-reshape-stock-market/docview/2438859397/se-2?accountid=13598

papers used only one percentage as a large price movement, this paper will look at three different percentages, namely a large one-day drop/rise of 10, 15 and 20 percent or more.

There are several main findings of this research. No significant difference in the reaction of the stock returns after a large one-day drop between the period before and during the COVID-19 pandemic has been found. In both periods the stocks kept decreasing after the large one-day drop. On the other hand, for the reaction of the stock returns after a large one-day rise significant differences were found between the period before and during the pandemic. Before the COVID-19 pandemic the abnormal returns were not significantly different from 0. However, during the pandemic a reversal effect has been found. Belonging as a company to the best/worst performing industries during the COVID-19 pandemic had no significant effect on the cumulative abnormal return after a large one-day price movement. Therefore, the main conclusion of this paper is that only a difference in the short-term reaction of stock returns in the U.S. stock market after a large one-day price rise can be found when comparing the period before and during the COVID-19 pandemic.

The remainder of this Master Thesis is organized as follows: in chapter 2, a literature review on stocks returns following large price movements and the effect of the COVID-19 pandemic on the financial markets is presented. The hypotheses associated with this research are also explained in this chapter. In chapter 3, the data that is used in this research is explained. The methodology will be described in chapter 4. Chapter 5 discusses the empirical findings to answer the hypotheses. Finally, in chapter 6 the conclusions of the paper will be described and provides possible recommendations for future research.

2 Literature Review

2.1 *Stock returns following large price movements*

According to Fama (1965, 1970) and the Efficient Market Hypothesis stock prices are traded at their fair market value because they fully reflect all available information. One of the three different degrees of the Efficient Market Hypothesis is the weak form efficiency, which claims that past price movements, volume and earnings data do not affect a stock's price and can't be used to predict its future direction. However, multiple studies have found evidence that stock prices react on large preceding price movements, which is in principle evidence against the weak form efficiency. In this section some of the results of these papers will be discussed.

2.1.1 Long-term reaction of stocks to large preceding price movements

De Bondt and Thaler (1985) were one of the first that have examined the long-term reaction of stocks to large preceding price movements. They found empirical evidence that extreme movements in stock prices are followed by subsequent price movements in the opposite direction. Their results showed that portfolios of stocks that performed worse than the market over a period of 36 months, would outperform the market by 19.6% in the next 36 months. For portfolios of stocks that had outperformed the market over a period of 36 months, the effect was much smaller. These portfolios earned about 5% less than the market in the next 36 months. Apparently, the overreaction effect is asymmetric, for prior losers the reversal is much larger than for prior winners. Another notable aspect of their findings was that the overreaction phenomenon mostly occurred during the second and third year of the test period. Furthermore, they found that most of the excess returns for the 'loser' portfolios were realized in January, whereas the 'winner' portfolios gained value at the end of the year and lost some in January.

Chan (1998) offered an alternative interpretation of the evidence on the performance of the contrarian strategy, a strategy that consists of buying stocks that have been losers and selling short stocks that have been winners. According to Chan, the risks of winner and loser stocks are not constant over time. Stocks whose value diminishes become riskier for many reasons. As suggested by the size-effect literature, market value is a good proxy for risk. The loser stocks were safer in the beginning but become riskier than winners by the end of the formation period. The risk of the firm may also increase as firm value falls because of the loss of economies of scale and increase in operating leverage. Chan has found that the risk of the contrarian strategy appears to correlate with the level of expected market-risk premium. Therefore, the estimation of abnormal returns may be sensitive to how the risks are estimated. Chan did not find evidence in support of the overreaction hypothesis.

2.1.2 Short-term reaction of stocks to large preceding price movements

Another way the predictability of stock returns after large price changes has been studied, is the analysis of stock returns following large one-day stock price movements. According to Bremer and Sweeney (1991), the observed daily stock returns after a large negative one-day rate of return are significantly larger than average on the following days. For a 10% fall, the return above average is 1.773% for the day after and rises cumulatively to 2.215% by the second day. This long recovery period of the stock price reversal is inconsistent with the efficient market hypothesis. Market illiquidity may partially explain their findings, but only for the day 1 rebound. Although the evidence of the reversal phenomenon is robust and distinct from other anomalies such as the weekend and turn-of-the-year effect, the effect does not represent abnormal profit opportunities.

Cox and Peterson (1994) also tried to explain the stock return behaviour following large one-day declines. Although they found significant reversals, the findings were not suggestive of short-term overreaction yielding profitable trading strategies. A substantial part of the reversal was due the bid-ask bounce, the large one-day price decline is associated with substantial selling and a closing transaction at bid price, this is leading to a reversal the next day. Further, they found that smaller firms reverse more than larger firms and that stocks with greater initial large declines do not have significant bigger subsequent reversals. According to Cox and Peterson, the degree of reversals tends to decrease when market liquidity is increased. On the longer term, they found that beginning four days after the drop, the stocks tend to enter a prolonged period of relatively poor performance where the previous reversal is itself reversed.

2.2 *Explanations of stock reactions to large preceding price movements*

In the section above light has been shed on a few studies that studied the reaction of stock returns to large preceding price movements in the short- and long-run. They all found price reversals after large price movements but the explanations for these price reversals were all different. In the section below explanations regarding market microstructure, risk premium and behaviour of market participants are discussed, which are, according to Amini et al. (2013), the main categories of explanations. It also appears that not all studies find price reversals, some studies find price continuations and some studies find a mix of reversals and continuations. This is unsurprising as Plastun (2021) found that financial markets evolve and can be inefficient from time to time. Therefore, it is possible that sometimes a momentum strategy can be profitable and sometimes a contrarian strategy can be profitable. This result supports the Adaptive Market Hypothesis of Lo (2004).

2.2.1 Bid-ask bounce effect

One of the market microstructure explanations is the bid-ask bounce effect. Some studies, such as Cox and Peterson (1994) and Park (1995), have found that this bid-ask bounce is the primary driver of the observed reversals in stock prices after large price changes. They argue that a large one-day decline is likely to be associated with substantial selling pressure. This means that there is an increased probability that a closing transaction is at bid price, this will lead to a reversal the next day due to the bid-ask bounce and can induce spurious negative serial correlation in stock returns. For a large one-day increase the substantial buying pressure will increase the probability that a closing transaction is at ask price, this again will lead to a reversal the next day due to the bid-ask bounce.

However, results in other studies are mixed and most of the later studies found no evidence that price reversals are caused by the bid-ask bounce. Liang and Mullineaux (1994) found that the bid-ask bounce explains at least a part of their results. Bharati et al. (2009) have researched partially the same period and stocks (from 1963 to 2003 and all stocks of NYSE, AMEX and NASDAQ) as Cox and Peterson (1994) and Liang and Mullineaux (1994) and found no evidence of price reversals that are caused by the bid-ask bounce. Choi and Jayaraman (2009) studied the period from 1996 to 2004 and also ruled out the explanation of the bid-ask bounce effect. A possible explanation for the disappearance of evidence on the bid-ask bounce effect could be because of the decline in the bid-ask spread over time, causing a non-significant bid-ask bounce effect.

2.2.2 Increased risk premium

Another field of explanations of the reaction of the stock prices after a large price movement, is the increase of the risk premium. Large price changes are associated with periods of elevated variance and thus risk. An increase of risk should be rewarded with a higher expected return of an investment. This means that prices will reflect their true value after a large price movement, this is in line with the Efficient Market Hypothesis. Two different kinds of explanations with regard to an increased risk premium are now discussed.

One of the papers that explained the price patterns they observed, as a rational response to risk, is Brown et al. (1988). They developed the Uncertain Information Hypothesis, which suggests that stocks will eventually increase after both favourable and unfavourable surprising news that also increases systematic risk. For favourable news the price of a stock will increase but this will be damped because of the increased risk premium. After uncertainty about the future has resolved the stock price will increase further. For unfavourable news the price of a stock will decrease and will decrease even further because of the increased risk premium. When the additional uncertainty has decreased the stock price will recover partially. So, the Uncertain Information Hypothesis predicts overreaction after large price drops and underreaction after large price rises. Results in other studies are mixed, some authors, such as Bremer and Sweeney (1991) have interpreted their results as support of the Uncertain Information Hypothesis while they have only investigated the stock returns after large drops. Other studies, such as Rezvanian et al. (2011), Yu et al. (2010), and Schnusenberg and Madura (2001) find evidence in favour of the Uncertain Information Hypothesis for both large price drops and large price rises. It should be noted that for all these studies, just like Brown et al. (1988), the definition of a large movement in stock price was quite small. Most studies, like Pham et al. (2007), Corrado and Jordan (1997), Lobe and Rieks (2011) and Atkins and Dyl (1990), that used a higher percentage as definition of a large movement in stock price, find for both large price drops and large price rises a reversal in price.

The other explanation with regard to the increased risk premium focusses on liquidity issues. Zawakowski et al. (2006) found reversals for both negative and positive price shocks and suggested that the few investors who are willing to accommodate the selling/buying pressure by providing liquidity after large price movements will be rewarded with excess return. The existence of an overreaction does not pose a threat to market efficiency, but it can be viewed as the correct reward for providing liquidity in a turbulent environment, where the behaviour of investors towards risk changes. Cox and Peterson (1994) and Mazouz et al. (2012) confirmed this by arguing that trading is not profitable due to liquidity exposure. Lasfer et al. (2003) found that the reaction of stocks following large price movements is related to market liquidity, heavier reactions were found in less-liquid markets. This indicates that liquidity providers are rewarded, thus ensuring market efficiency.

2.2.3 Over- and underreaction hypotheses

The last explanation of the reaction of stock returns after large price movements that will be discussed, is the behavioural explanation. It is not strange that emotions are running highest and perhaps rationality is most elusive in times that stock prices make large movements. Therefore, the effect of extreme price movements is an interesting subject when it comes to behavioural biases. Two contrasting behavioural hypotheses come forward when it comes to explaining the reaction of stock returns after large price movements.

The first hypothesis is the overreaction hypothesis. The concept of the overreaction theory is known for years, and many researchers have tried to explain this. A study in experimental psychology by Kahneman and Tversky (1973) finds that when people evaluate probability by representativeness, prior probabilities will be neglected. This is in violation with the Bayes' Rule, which prescribes the correct reaction to new information. Individuals tend to overweight recent information and underweight prior data and therefore tend to overreact to unexpected and dramatic events. An investment strategy to generate excess returns that would fit with the overreaction hypothesis is the contrarian strategy, buying losers and selling short winners. De Bondt and Thaler (1985) were one of the first that have examined the long-term reaction of stock returns to large preceding price movements. They found that excessive stock price movements resulted in subsequent stock price reversals. Most papers, like Akhigbe et al. (1998), Pham et al. (2007), Lobe and Rieks (2011), Otchere and Chan (2003) attributed the overreaction theory as explanation to the price reversals. However, they also found that it’s not possible to make economic profits after accounting for transaction costs. Ma et al. (2005), on the other hand, argue that in their sample the two-days cumulative abnormal return of 4.5% for NASDAQ losers would cover transaction costs. In this sample they looked to the top gainer and loser from each market every day. Piccoli et al. (2017) found evidence that stocks tend to overreact after both positive and negative events, but, just like the other papers, in a more pronounced way in the latter case. When the market exhibits clustered extreme swings the overreaction effect is more intense, indicating that the overreaction and market volatility are related. Caporale and Plastun (2019) found that the frequency of overreactions is highly correlated to the volatility index (VIX). Therefore, the frequency of overreactions could be used as an alternative measure of market sentiment. They also found that the frequency of overreactions is informative about crises, a sharp increase in the number of overreactions is associated with a crisis period.

The second behavioural explanation is the underreaction hypothesis. This hypothesis proposes that news is slowly incorporated into prices causing stock prices to move in the direction of the initial price change. An investment strategy to generate excess returns that would fit with this hypothesis is called the momentum strategy, buying winners, and selling short losers. Hudson et al. (2001) found evidence of underreaction for price changes smaller than 5% in absolute value, for prices changes bigger than 5% limited support for the overreaction hypothesis was found. Mazouz et al. (2009) found evidence for underreaction for positive shocks of all sizes and for small negative shocks. Plastun et al. (2021) studied the evolution of price effects. The results suggest that between 1940 and 1980, a strong momentum effect after positive price shocks was present, and that it was possible to generate abnormal profits from trading. Their results also suggest that academic publications about abnormal stock returns after large price movements may have contributed to their disappearance from the US stock market.

2.3 COVID-19 pandemic

On January 30, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak to be a global emergency. Since the outbreak of the COVID-19 virus around the world, life is not the same anymore. To prevent the virus spreading around the population, governments imposed multiple restrictions. These restrictions on commercial activity are more stringent, broader in scope, more widespread, and lengthier in duration than policy responses to the Spanish Flu and completely unlike the governmental response to the 1957-58 and 1968 influenza pandemics. Some industries have been hit hard because of these restrictions. Albulescu (2020) found that even in the pre-pandemic phase, COVID-19 had severely affected the economy in a negative way.

As mentioned before, Plastun et al. (2021) found that before the Global Financial Crisis a momentum strategy was a profitable strategy after large stock price movements. However, during and after the Global Financial Crisis the profitable strategy changed in a contrarian strategy. He claims that one of the possible reasons for the evolution of financial markets can be crisis periods. It is therefore of vital importance to examine whether the consequences of the COVID-19 crisis can result in an evolution of financial markets. In this section the consequences of the COVID-19 crisis on the financial markets are discussed.

2.3.1 COVID-19 Stock market crash

The dramatic stock market crash in March 2020 was a unique and completely different to the 2008 crash as it did not reflect the bursting of an asset price bubble. Instead, it was the result of a global health crisis. In only four trading days, the Dow Jones Industrial Average plunged 6,400 points. A decrease of almost 26%. Mazur (2021) found that 90% of the S&P1500 stocks generated large negative returns. Firms in the crude petroleum sector were hit hardest and lost 60% of their market value in one day. Also, stock returns in industries such as scheduled passenger air transportation, entertainment and hospitality fell dramatically. However, stocks in some industries such as food, trucking & courier services, and software earned high positive returns, the superior performers in these industries have had a positive monthly return of 20% or more. Ashraf (2020) showed that the number of confirmed COVID-19 cases to be negatively correlated with the stock market returns in the first 3 months of 2020. At first, the Federal Reserve (FED) responded with a zero-percent interest rate policy and at least a $700 billion quantitative easing program, but because of the negative responses to this policy the Federal Reserve announced an unlimited quantitative easing policy eight days later. Zhang et al. (2020) found that these non-conventional policy interventions create further uncertainty and may cause long-term problems. This uncertainty causes the market to become highly volatile and unpredictable. Yousfi et al. (2021) found in both the first and second wave of the COVID-19 outbreak in the United States a significant degree of coherence between the US stock market return and US uncertainty and the COVID-19 pandemic. During the second wave this coherence was more significant and meaningful than during the first wave.

2.3.2 COVID-19 pandemic and stock market volatility

Baker et al. (2020) examined the impact of the outbreak of the COVID-19 virus on the stock market. They found that the volatility levels in the middle of March 2020 rivalled or surpassed those last seen in October 1987 and December 2008 in the United States. After April, the volatility decreased but remained well above pre-pandemic levels. A potential explanation of the daily stock market jumps and high stock market volatility, is that information about pandemics is richer and diffuses much more rapidly now than during the Spanish Flu. Zaremba et al. (2020) found two types of actions, with regard to stringent policy responses, that are major contributors to the growth of volatility. Information campaigns about COVID-19 and the cancellation of public events have a significant effect to the growth of volatility, even when is controlling for the growth of number of infections and deaths. Baek et al. (2020) found that both positive and negative news about COVID-19 has had significant impact on the US stock market volatility. Changes in volatility were more sensitive to COVID-19 news than economic indicators. However, Uddin et al. (2021) found that factors such as economic resilience, intensity of capitalism, level of corporate governance and financial development of a country could reduce the increased stock market volatility due to the COVID-19 pandemic. Monetary policy response of the central banks, on the other hand, increased the market variance. At industry level, utilities and the oil and gas industry experienced some of the largest shifts in market risk. This is unsurprisingly as Alfaro et al. (2020) found that more capital-intensive and leveraged industries are likely to experience the larger shifts in market risk. Shifts in market risk are related to uncertainty about the duration of the lockdowns and the impact on demand. Smales (2021) found that the Google search volume (GSV) for the word 'coronavirus' represents retail investor attention. The author argued that institutional investors have access to a variety of professional news sources and therefore do not have to rely on Google searches. The results suggested that the Google search volume and thus retail investor attention negatively influences stock index returns and is associated with higher volatility.

2.4 Research hypotheses

After analysing the literature about the reaction of stock returns following large price movements and the consequences of the COVID-19 pandemic for the stock market, the following hypotheses can be made:

H1: For large one-day stock price rises a significant price reversal effect in the short-run will follow in the year prior to the COIVD-19 pandemic.

H2: For large one-day stock price drops a significant price reversal effect in the short-run will follow in the year prior to the COIVD-19 pandemic.

Most studies have found a price reversal effect after large one-day stock price drops and rises therefore it is most obvious to also expect a price reversal effect in the year prior to the COVID-19 pandemic.

H3: For large one-day stock price rises a significant price reversal effect in the short-run will follow in the year during the COIVD-19 pandemic.

H4: For large one-day stock price drops a significant price reversal effect in the short-run will follow in the year during the COIVD-19 pandemic.

If a reversal effect is expected in the year prior to the COVID-19 pandemic, it is also expected that during the COVID-19 pandemic stock returns will reverse following a large one-day price movement. Multiple authors wrote about the increased stock market volatility during the COVID-19 pandemic and according to Piccoli et al. (2017) and Caporale and Plastun (2019) high volatility and the number of overreactions are highly correlated.

H5: The cumulative abnormal returns in the short-run following large one-day price rises during the COVID-19 pandemic are significantly different from the cumulative abnormal returns in the short-run following large one-day price rises before the COVID-19 pandemic.

H6: The cumulative abnormal returns in the short-run following large one-day price drops during the COVID-19 pandemic are significantly different from the cumulative abnormal returns in the short-run following large one-day price drops before the COVID-19 pandemic.

Piccoli et al. (2017) found that the overreaction effect is more intense when the market exhibits clustered extreme swings. During the COVID-19 pandemic the market exhibits clustered extreme swings and in the year prior to the pandemic the market was relatively calm. Therefore, the expectation is that the reversal effect will be significantly bigger during the pandemic compared to the year preceding the pandemic. Another option could be, in line with the findings of Plastun et al. (2021), that due to the COVID-19 crisis an evolution in the financial markets has started and therefore the profitable strategy has turned 180 degrees. Consequently, that the cumulative abnormal returns are significantly different from the pre-pandemic cumulative abnormal returns.

H7: The reversal effect in the short-run following a large one-day price rise will be significantly smaller for stocks that belong to the best performing industries during the COVID-19 pandemic.

H8: The reversal effect in the short-run following a large one-day price drop will be significantly bigger for stocks that belong to the best performing industries during the COVID-19 pandemic.

H9: The reversal effect in the short-run following a large one-day price rise will be significantly bigger for stocks that belong to the worst performing industries during the COVID-19 pandemic.

H10: The reversal effect in the short-run following a large one-day price drop will be significantly smaller for stocks that belong to the worst performing industries during the COVID-19 pandemic.

Stocks that belong to the best performing industries (i.e. technology, software, courier services) during the COVID-19 pandemic have outperformed the market. Therefore, they are more likely to keep outperforming the market. When a stock that belongs to the best performing industries had a large one-day price rise, it is less likely that this stock will reverse. However, if the stock had a large one-day price decrease it is more likely to reverse. The opposite is true for stocks that belong to the worst performing industries during the pandemic.

3 Data

In this section, the dataset that is used to test the hypotheses, will be described. Furthermore, will this section describe the length of each period and certain choices to exclude some months in the dataset, explain about how the events of one-day price movements are selected and describes the characteristics of the dataset.

3.1 Data collection

Daily stock returns of all firms of the New York Stock Exchange are analysed in this event study. Daily closing prices have been obtained through Compustat – Capital IQ, which was accessed through Wharton Research Data Services. The reason to choose the New York Stock Exchange is because it is the largest stock exchange in the world. The two periods that are used in this study are relative short compared to other papers. Therefore, it was important to choose an exchange with a lot of securities to increase the change of an event. Furthermore, most studies have used the New York Stock Exchange as stock exchange for the dataset, so therefore it is easier to compare these papers to see if similarities can be found.

The two periods that are examined, each consist of 12 months. The period prior to the COVID-19 pandemic is from November 2018 to October 2019 and has a total of 252 trading days. It was necessary to end the pre-COVID period 'already' in October 2019, and not just before the beginning of the pandemic, because to calculate the abnormal returns, some post-event parameters needed to be calculated and therefore at least 60 trading days after the event were required. The period during the COVID-19 pandemic is from April 2020 to March 2021 and has a total of 251 trading days. For the calculation of the abnormal returns, some pre-event parameters needed to be calculated. The months February and March 2020 are excluded from this calculation because of the significant volatility surrounding the stock market crash in these months due to the COVID-19 pandemic.

Daily stock returns following one-day price decrease/increase of 10, 15 and 20 percent or more are examined. The trigger of 10% is used in many studies (see for example, Bremer and Sweeney (1991), Choi & Jayaraman (2009), and Peterson (1995)). However, with the increased volatility during the COVID-19 period it may also be interesting to see if the results differ when triggers that are higher than 10% are used. Therefore, triggers of 15 and 20 percent are used as well. According to Bremer and Sweeny (1991), it is possible that very low-priced stocks may have large negative rates of return, followed by reversals, that actually only reflects oscillation between bid and ask prices. In order to prevent this potential bias, only stocks that have prices of at least $10 per share prior to the event are included. To minimize across-sample correlation, only one event per day is allowed. For days with more than one event, the observation that appears first in alphabetic sort will be retained for that certain day, this approach is similar to the method used by Bremer and Sweeney (1991).

Mean returns and market model parameters are estimated over two different 100-trading-day estimation periods, which is consistent with the methodology of Cox and Peterson (1994). The pre-event period and the post-event period, in which the pre-event period is from 105 to 6 trading days prior to the event date and the post-event period from 21 to 120 trading days following the event date. As said before, for some of the calculations less than 100 trading days are used but for all the calculations a minimum of 60 trading days has been used. For the calculation of these parameters the return of the market was needed, this was not available on Compustat – Capital IQ. The return of the New York Stock Exchange Composite was therefore retrieved from Yahoo Finance.

In addition to collecting data on share prices, data on shares outstanding, CBOE Volatility Index (VIX), trading volume and North American Industry Classification System (NAICS) codes was also obtained. The data on shares outstanding will be used to calculate the market capitalization, which will be calculated 6 trading days prior to large one-day price movement. Data on the trading volume and the VIX are obtained on the event date itself. The NAICS codes of the stocks are obtained to categorize the stocks into three categories: best performing industries during the COVID-19 pandemic, worst performing industries during the COVID-19 pandemic and neither best nor worst performing industries during the COVID-19 pandemic. In Table 1 a list of the best performing industries can be seen and their NAICS codes. In Table 2 a list of the worst performing industries during the COVID-19 pandemic can be seen and their NAICS codes.

Table 1 NAICS Codes And Names Of the Best Performing Industries During the COVID-19 Pandemic

NAICS	Industry
212	Mining (expect Oil and Gas)
212210	Iron Ore Mining
212230	Copper, Nickel, Lead, and Zinc Mining
315240	Women's, Girls', and Infants' Cut and Sew Apparel Manufacturing
325199	All Other Basic Organic Chemical Manufacturing
325414	Biological Product (except Diagnostic) Manufacturing
325510	Paint and Coating Manufacturing
325612	Polish and Other Sanitation Good Manufacturing
326299	All Other Rubber Product Manufacturing
333111	Farm Machinery and Equipment Manufacturing
333120	Construction Machinery Manufacturing
334220	Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing
334413	Semiconductor and Related Device Manufacturing
334510	Electromedical and Electrotherapeutic Apparatus Manufacturing
334516	Analytical Laboratory Instrument Manufacturing
336111	Automobile Manufacturing
339112	Surgical and Medical Instrument Manufacturing
444110	Home Centres
452311	Warehouse Clubs and Supercentres
452319	All Other General Merchandise Stores
453998	All Other Miscellaneous Store Retailers (except Tobacco Stores)
454110	Electronic Shopping and Mail-Order Houses
492110	Couriers and Express Delivery Services
511210	Software Publishers
518210	Data Processing, Hosting, and Related Services
519130	Internet Publishing and Broadcasting and Web Search Portals
532412	Construction, Mining, and Forestry Machinery and Equipment Rental and Leasing
622110	General Medical and Surgical Hospitals
722513	Limited-Service Restaurants

Table 2 NAICS Codes And Names Of the Worst Performing Industries During the COVID-19 Pandemic

NAICS	Industry
221111	Hydroelectric Power Generation
221210	Natural Gas Distribution
314110	Carpet and Rug Mills
315	Apparel Manufacturing
324110	Petroleum Refineries
325620	Toilet Preparation Manufacturing
333316	Photographic and Photocopying Equipment Manufacturing
334112	Computer Storage Device Manufacturing
334511	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical System and Instrument Manufacturing
336412	Aircraft Engine and Engine Parts Manufacturing
336414	Guided Missile and Space Vehicle Manufacturing
446120	Cosmetics, Beauty Supplies, and Perfume Stores
447190	Other Gasoline Stations
448140	Family Clothing Stores
452210	Department Stores
481111	Scheduled Passenger Air Transportation
483112	Deep Sea Passenger Transportation
486210	Pipeline Transportation of Natural Gas
522110	Commercial Banking
523920	Portfolio Management
524113	Direct Life Insurance Carriers
524114	Direct Health and Medical Insurance Carriers
531110	Lessors of Residential Buildings and Dwellings
531120	Lessors of Non-residential Buildings (except Mini warehouses)
721110	Hotels (except Casino Hotels) and Motels

3.2 Characteristics of the dataset

In Table 3 the characteristics of the four datasets can be found. The most interesting observations and differences will be discussed below.

It can be seen that the number of large one-day price drops was slightly smaller during the COVID-19 pandemic than before the pandemic, 183 versus 194 for the 10% trigger. However, the number of large one-day price rises is considerably higher during the pandemic compared to before the pandemic, 222 versus 172 for the 10% trigger. Furthermore, it is noticeable from Table 3 that both the pre- and post-event mean daily returns during the COVID-19 pandemic were higher than before the pandemic. This is not surprising when looking at Figures 1 & 2, where it can be seen that the return of the NYSE composite was considerably higher during the COVID-19 pandemic than before.

The matched pair t-statistics of mean differences show that most post-event characteristics don't differ significantly from the pre-event characteristics. However, for the dataset with large one-day price rises during the COVID-19 pandemic, all post-event characteristics for both the 10, 15 and 20 percent trigger differ significantly at the 5 percent level. Panel B in Table 3 shows that during the pandemic the average daily returns and the market model alphas in the post-event period are significantly lower than during the pre-event period, this could indicate that a large price increase may be the last breath of a period of good stock performance. Although this economic change is immaterial, it may also be noteworthy that the betas in the post-event period are significantly higher than during the pre-event period.

In spite of the fact that most post-event characteristics do not differ significantly from the pre-event characteristics it is still interesting to take a look at these numbers. In Panel B it can be seen that the post-event mean daily return for large one-day price rises before the pandemic, is for both the 10, 15 and 20 percent trigger slightly (not significant) higher than the pre-event mean daily return. However, as said before, during the pandemic the post-event mean daily return for large one-day price rises is considerably (significant) lower than the pre-event mean daily return. A similar effect can be seen in Panel A for the 15 and 20 percent trigger. Even though the difference between pre- and post-event mean daily return is not significant, it can be seen that the post-event mean daily return is slightly higher than the pre-event mean daily return before the COVID-19 pandemic. However, during the pandemic it can be seen that the post-event mean daily return is lower than the pre-event mean daily return. This change could be a first sign of an evolution in the financial markets, consistent with the findings of Plastun et al. (2021). They argued that a period of crisis is a possible reason for evolutions in financial markets.

Furthermore, it can be seen that the market capitalization of the stocks that have perceived a large one-day price drop is higher than the stocks that have perceived a large one-day price rise, both before and during the pandemic. Trading volume and the VIX on the event day are much higher during the pandemic than before the pandemic.

Table 3: Characteristics Of The Datasets Having Large One-Day Price Movements

In Panels A and B the characteristics of four datasets can be found. The characteristics of the Pre-COVID-19 datasets consists of data from November 2018 to October 2019 and the characteristics of the COVID-19 datasets consists of data from April 2020 to March 2021. All characteristics are averages of the output of the data. The pre-event period is from 6 to 105 trading days prior to the event day and the post-event period from 21 to 120 trading days after the event day. The market return is based on the NYSE composite (NYA). Market capitalization is calculated 6 trading days prior to the large one-day price movement. Characteristics of the Trading Value and CBOE Volatility index are from the event day itself.

Panel A	Drop Pre-COVID-19			Drop COVID-19		
Characteristic	10% (n=194)	15% (n=123)	20% (n=75)	10% (n=185)	15% (n=126)	20% (n=78)
Pre-event mean daily return	0.44%	-0.060%	-0.049%	0.951%	2.596%	1.403%
Post-event mean daily return	0.029%*	0.019%	0.040%	0.370%	0.324%*	0.316%
Pre-event market model alpha	0.411%	-0.075%	-0.068%	0.777%	2.443%	1.260%
Post-event market model alpha	-0.047%*	-0.066%	-0.037%	0.210%	0.154%*	0.176%
Pre-event market model beta	1437	1.442	1.411	1.130	0.977	0.982
Post-event market model beta	1,.560	1.588*	1.602*	1.283	1.345*	1.264
Day 0 return	-14.841%	-23.015%	-27.799%	-15.578%	-23.415%	-31.632%
Day 0 market return	-0.072%	-0.243%	-0.122%	0.032%	-0.040%	-0.134%
Market Capitalization (billions of dollars)	10.09	7.99	7.82	9.50	8.68	11.91
Trading Volume (millions of shares)	7.58	12.61	14.70	14.18	16.39	24.77
CBOE Volatility Index (VIX)	16.65	17.16	17.16	27.60	27.75	27.79

Panel B	Rise Pre-COVID-19			Rise COVID-19		
Characteristic	10% (n=172)	15% (n=89)	20% (n=48)	10% (n=222)	15% (n=184)	20% (n=121)
Pre-event mean daily return	-0.020%	-0.058%	-0.102%	1.135%	1.630%	1.809%
Post-event mean daily return	-0.001%	0.041%*	0.032%	0.326%*	0.319%*	0.293%*
Pre-event market model alpha	-0.033%	-0.070%	-0.066%	0.928%	1.453%	1.646%
Post-event market model alpha	-0.064%	-0.044%	-0.067%	0.113%*	0.128%*	0.114%*
Pre-event market model beta	1.361	1.404	1.488	1.350	1.184	1.134
Post-event market model beta	1.402	1.518	1.613	1.601*	1.476*	1.446*
Day 0 return	14.651%	20.903%	25.577%	15.011%	20.775%	27.523%
Day 0 market return	0.131%	0.193%	0.267%	0.233%	0.313%	0.430%
Market Capitalization (billions of dollars)	4.06	3.08	3.00	5.87	4.77	4.94
Trading Volume (millions of dollars)	3.86	8.12	8.58	12.04	19.87	30.07
CBOE Volatility Index (VIX)	16.49	16.58	16.39	27.42	27.16	27.14

* Matched pair t-statistics indicates that the post-event parameter significantly differs from the pre-event parameter at the 0.05 level.

Figure 1: Return New York Stock Exchange Composite Before COVID-19 Pandemic

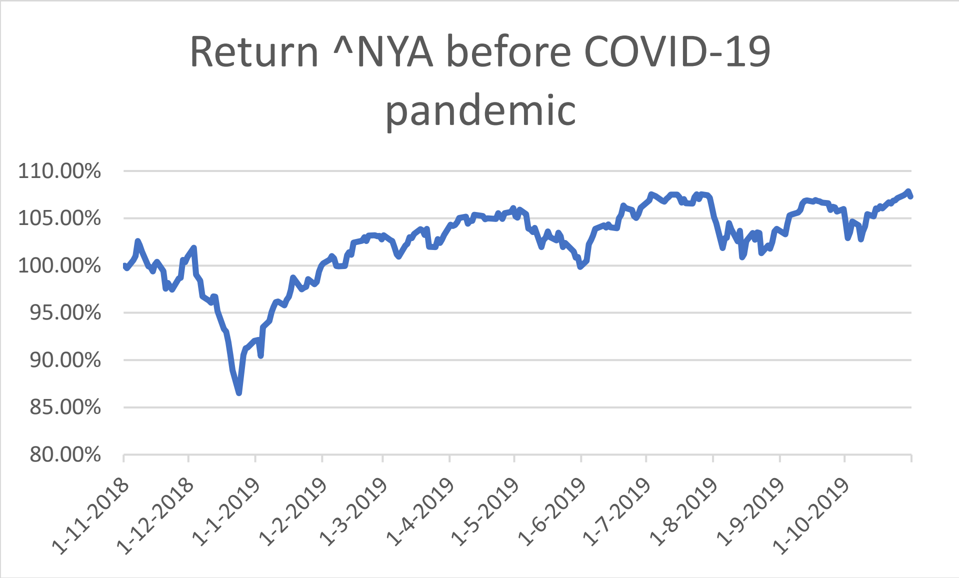
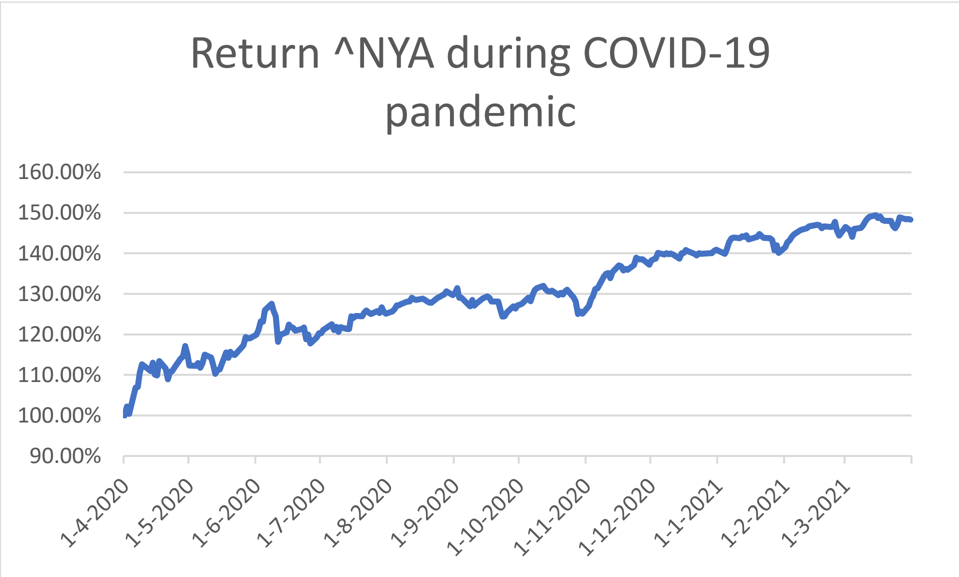


Figure 2: Return New York Stock Exchange Composite During COVID-19 Pandemic



4 Methodology

In this section, the methodology of the research will be discussed. First, the calculations of the cumulative abnormal return (CAR) will be explained. Then, the statistical test that has been used to compare the results will be explained. At last, the regression model, that has been made to test whether the best and/or worst performing industries have a significant impact on the cumulative abnormal return, will be discussed. This paper studies the short-time reaction of the stock return after a large one-day price movement. The assumption is that the short-term ends 20 trading days after the event day, this assumption is consistent with the papers that have been analysed in this paper.

4.1 Cumulative abnormal return

In order to test all four hypotheses in this research, cumulative abnormal returns need to be calculated. For the calculation of the cumulative abnormal return, the abnormal returns are needed. In this research abnormal returns are measured with a variation of the market model approach. In this variation of the market model approach an average of the pre-event alpha and post event alpha and an average of the pre-event beta and post-event beta has been used. So, to calculate the abnormal returns, firm specific market model parameters of the pre- and post-event period have been calculated. To calculate these parameters the following formula has been used:

$$R_{i,t} = a_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

With the following assumption:

$$E(\varepsilon_{i,t}) = 0 \quad Var(\varepsilon_{i,t}) = \sigma^2$$

Where $R_{i,t}$ is the return of the company's stock *i* at time *t*, where t=T-106 to T-7 and T+21 to T+120. $R_{m,t}$ is the return of the market index at time *t*, the New York Stock Exchange composite (^NYE) is used as market index. $\varepsilon_{i,t}$ is the error term and is assumed to be normally distributed. With the average alpha and beta it was possible to calculate the abnormal returns with the following formula:

$$AR_{i,t} = R_{i,t} - (\bar{a}_i + \bar{\beta}_i R_{m,t})$$

So, basically the abnormal return is equal to the return of the security minus an average of alpha and minus an average of beta times the return on the market. Subsequently, to calculate the cumulative abnormal return the following formula has been used:

$$CAR_{i,t} = \sum_{t-5}^{t+20} AR_{i,t}$$

The cumulative abnormal return has been calculated for different event windows. The biggest window is 26 trading days, from 5 days before the event day to 20 days after the event day. Calculations are also made from 1 to 3, 4 to 20 and 1 to 20 trading days after the event day. The cumulative abnormal return will not be calculated after 20 trading days because this thesis studies only the short-term effects after a large one-day price movement. To show these results in a figure or table, the average (cumulative) abnormal returns of all securities have been calculated. This has been done for the pre-pandemic period and the pandemic period for both large one-day price rises and large one-day price drops of 10% or more. Robustness checks have been conducted with triggers of 15% and 20%.

In Table 4 and Figures 3 and 4 the difference between the pre-pandemic and pandemic cumulative abnormal returns can been seen. In Figure 3 it can be seen that the reaction after a large one-day drop is quite the same, in both periods the cumulative abnormal return keeps declining. The difference is in the period before the drop, where the cumulative abnormal return during the pandemic has risen to 5% while the cumulative abnormal return before the pandemic stayed almost flat. In Figure 4 it can be seen that the reaction after a large one-day rise is completely different between the pre-pandemic and pandemic cumulative abnormal returns. The cumulative abnormal return during the COVID-19 pandemic shows a big reversal after the large one-day rise, while the cumulative abnormal return before the pandemic remained relatively flat.

Table 4 (Cumulative) Abnormal Return Following A Large One-Day Price Movement Before and During the COVID-19 Pandemic

In Panels A and B the characteristics of four datasets can be found. The characteristics of the Pre-COVID-19 datasets consists of data from November 2018 to October 2019 and the characteristics of the COVID-19 datasets consists of data from April 2020 to March 2021. All characteristics are averages of the output of the data. Abnormal returns is equal to the return of the security minus an average of alpha and minus an average of beta times the return on the market.

Panel A	Drop Pre-COVID-19			Drop COVID-19		
Characteristic	10% (n=194)	15% (n=123)	20% (n=75)	10% (n=185)	15% (n=127)	20% (n=78)
Abnormal Return Day 0	-14.793%	-22.537%	-27.488%	-15.966%	-24.523%	-32.082%
Abnormal Return Day 1	-0.617%	-0.780%	-0.093%	-0.864%	-1.990%	-1.463%
Abnormal Return Day 2	-0.050%	0.806%	1.062%	0.049%	-1.517%	-0.619%
Abnormal Return Day 3	0.400%	-0.147%	-0.081%	-0.392%	-1.539%	-0.052%
Cummulative Abnormal Return Day 1-3	-0.266%	-0.121%	0.888%	-1.208%	-5.046%	-2.134%
Cummulative Abnormal Return Day 4-20	-6.403%	0.786%	0.021%	-4.324%	-20.594%	-10.637%

Panel B	Rise Pre-COVID-19			Rise COVID-19		
Characteristic	10% (n=172)	15% (n=89)	20% (n=48)	10% (n=222)	15% (n=184)	20% (n=121)
Abnormal Return Day 0	14.440%	20.589%	25.000%	13.864%	19.429%	25.983%
Abnormal Return Day 1	0.105%	-0.467%	-0.606%	-0.711%	-0.635%	-0.510%
Abnormal Return Day 2	-0.048%	-0.389%	-0.628%	-0.433%	-1.509%	-1.464%
Abnormal Return Day 3	0.066%	0.134%	0.051%	-0.199%	-0.904%	-1.311%
Cummulative Abnormal Return Day 1-3	0.123%	-0.722%	-1.183%	-1.343%	-3.048%	-3.284%
Cummulative Abnormal Return Day 4-20	-0.968%	-0.403%	1.382%	-10.500%	-11.146%	-10.824%

Figure 3 Cumulative Abnormal Returns Following a Large One-Day Drop of 10% Before And During the COVID-19 Pandemic

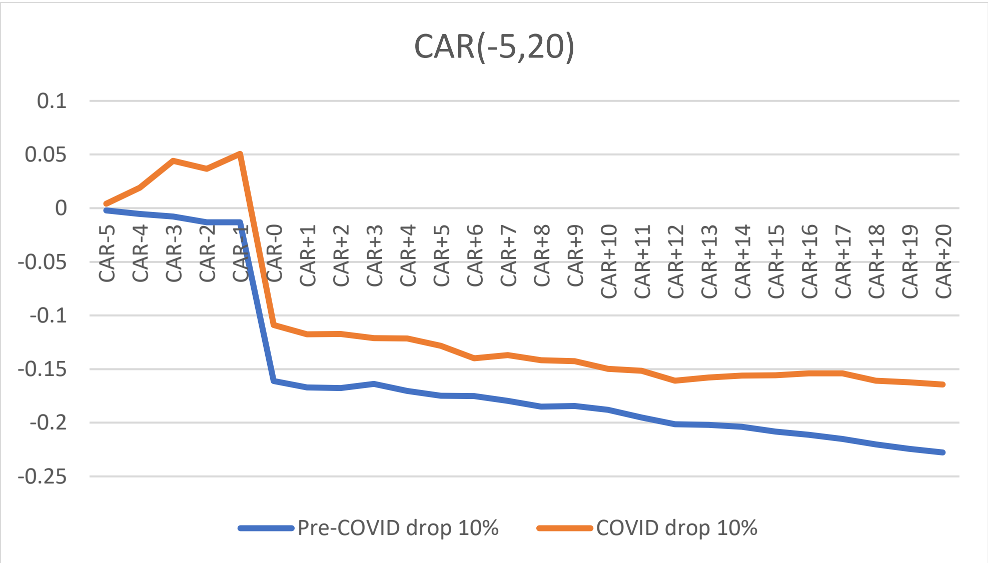
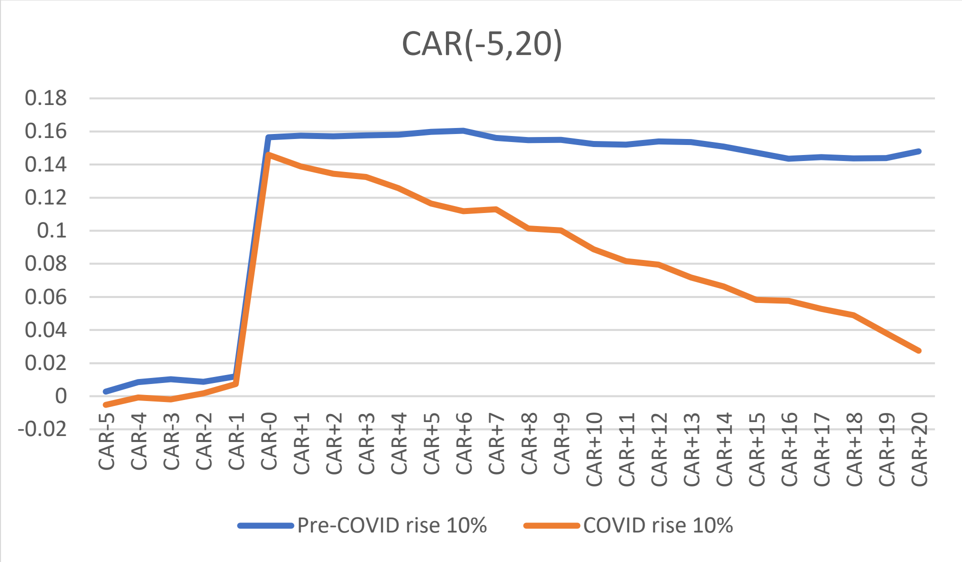


Figure 4 Cumulative Abnormal Returns Following a Large One-Day Rise of 10% Before And During the COVID-19 Pandemic



4.2 Statistical tests

Hypotheses 1, 2, 3 and 4 have been tested, to find out whether a reversal effect will follow after a large one-day price movement for both the period before and the period during the COVID-19 pandemic, by conducting multiple One-Tailed, One-Sample t-Tests. To test Hypotheses 1, 2, 3 and 4, a One-Tailed, One-Sample t-Test had to be run 12 times for every CAR event window. The first six times were to find out if the cumulative abnormal return following a large one-day price drop for both before and during the COVID-19 pandemic was significantly higher than 0 for all three triggers (10, 15 and 20 percent drop). The last six times were to find out if the cumulative abnormal return following a large one-day price rise for both before and during the COVID-19 pandemic was significantly lower than 0 for all three triggers (10, 15 and 20 percent rise).

To test Hypotheses 5 and 6, a Two-Tailed, Two-Sample t-Test had to be run six times for every CAR event window. The first three times were to find out if the cumulative abnormal returns following a large price drop during the COVID-19 pandemic were significantly different from the cumulative abnormal returns following a large price drop before the COVID-19 pandemic for all three triggers (10, 15, 20 percent drop). The last three times were to find out if the cumulative abnormal returns following a large price rise during the COVID-19 pandemic were significantly different from the cumulative abnormal returns following a large price rise before the COVID-19 pandemic for all three triggers (10, 15, 20 percent rise).

4.3 Regression model

To test whether the cumulative abnormal return is different for securities in the best and/or worst industries, a regression model has been made. Multiple OLS regressions will be conducted with CAR as dependent variable with different event windows. For these regressions only the stocks that have reversed following a large one-day price movement will be taken into account. This is because the distinction between the reversal of stocks of the best/worst performing industries during the COVID-19 pandemic and the reversal of all stocks is examined. The following regression has been constructed:

$$CAR_i = a + \beta_1 AR0 + \beta_2 SIZE + \beta_3 TV + \beta_4 VIX + \beta_5 D_{Worst\_Ind} + \beta_6 D_{Best\_Ind} + \varepsilon$$

The independent variables can be described as follows:

AR0: The abnormal return on the event day.

SIZE: The natural logarithm of the market capitalization 6 trading days prior to the event day.

TV: The natural logarithm of the trading volume on the event day.

VIX: The CBOE Volatility Index

D_{Worst_Ind}: A dummy variable that equals 1 if the security belongs to the worst performing industries during the COVID-19 pandemic and equals 0 otherwise.

D_{Best_Ind}: A dummy variable that equals 1 if the security belongs to the best performing industries during the COVID-19 pandemic and equals 0 otherwise.

ε: Error term with expected value of 0.

The OLS regression is made for six different specifications of the dependent variable, reflecting the abnormal return for day 1, 2 and 3 and the cumulative abnormal return for days 1 through 3, 1 through 20 and 4 through 20. The Breusch-Pagan / Cook-Weisberg test has been used for all estimations to test for heteroskedasticity. Robust standard errors have been used in case of heteroskedasticity. All estimations were tested for multicollinearity using the Variance Inflation Factor (VIF) as measure, however no multicollinearity has been found.

5 Results

In this section the results will be discussed and interpreted to answer the hypotheses. The results will be divided into 3 separate subsections. The first subsection will discuss and present the results of the abnormal return after a large one-day price movement for both the Pre-COVID and COVID period. The second subsection will discuss and present the results of the difference in abnormal return between the Pre-COVID and COVID period. The last subsection will discuss and present the results of the regression analyses and the industry effect.

5.1 (Cumulative) abnormal returns after a large one-day price movement

In Table 5, the results of the One-Tailed, One-Sample t-Test can be seen. In Panel A the results show that none of the (cumulative) abnormal returns following a large price drop before and during the COVID-19 pandemic were significantly higher than 0. The biggest reversal has been found for the abnormal return on the second trading day after the event of a one-day drop of 20% and is 0.91%. It can also be seen that before the COVID-19 pandemic more than half of these (cumulative) abnormal returns are positive. On the contrary, it can be seen that during the pandemic most (C)ARs are negative. So there, a momentum strategy seems more appropriate. Further, it can be seen that during the COVID-19 pandemic the cumulative abnormal returns were also negative during the 4-20 trading days period. This means that it takes multiple days to incorporate the event into the stock price, this is against the semi-strong form of the EMH of Fama (1970). Despite the increased stock market volatility during the COVID-19 pandemic, what according to Piccoli et al. (2017) and Caporale and Plastun (2019) would let to more reversals, the percentage of overreactions has not increased compared to the period before the COVID-19 pandemic. Taking all this in consideration, it can be concluded that no significant reversal effect can be observed after a large one-day price drop for both the period before the COVID-19 pandemic as for the period during the COVID-19 pandemic. Therefore, Hypothesis 2 – *For large one-day stock price drops a significant price reversal effect in the short-run will follow in the year prior to the COIVD-19 pandemic* – and Hypothesis 4 – *For large one-day stock price drops a significant price reversal effect in the short-run will follow in the year during the COIVD-19 pandemic* – can be rejected.

In Panel B the results show that none of the (cumulative) abnormal returns before the COVID-19 pandemic were significantly lower than 0. The biggest reversal has been found for the cumulative abnormal return from 1 trading day after the event day to 3 trading days after the event day for the 20% drop and is -1.18%. From this it can be concluded that no significant reversal effect can be observed after a large one-day price rise for the period before the COVID-19 pandemic. Therefore, Hypothesis 1 – F*or large one-day stock price rises a significant price reversal effect in the short-run will follow in the year prior to the COIVD-19 pandemic* – can be rejected. On the other hand, during the pandemic half of the (cumulative abnormal) returns are significantly different from 0. The cumulative abnormal returns during the 1-20 trading days period are all significantly different from 0 and are for the 10, 15 and 20 percent rise respectively -11.84%, -14.19% and -14.11%. This means that a significant reversal effect after 20 trading days of the large one-day rise has been found. This effect can also be seen in Figure 5, the large one-day rise of the 10% line is almost completely neutralized by the reversal effect. Therefore, it can be concluded that Hypothesis 3 – *For large one-day stock price rises a significant price reversal effect in the short-run will follow in the year during the COIVD-19 pandemic* – can be accepted.

Table 5 Results Of the One-Tailed, One-Sample t-Test Of (Cumulative) Abnormal Returns Following Large One-Day Price Movements

In Panels A and B the mean (cumulative) abnormal returns are presented. The CARs of the Pre-COVID-19 datasets consists of data from November 2018 to October 2019 and the CARs of the COVID-19 datasets consists of data from April 2020 to March 2021. T-values of the One-Tailed, One-Sample t-Test can be found in the parentheses and in the brackets the proportion of positive, for large one-day drops, and the proportion of negative, for large one-day rises, (cumulative) abnormal returns can be found. Day 0 is the date of the large price movement. Day 1 is one trading day after the event day and day 2 are two days after the event day and so forth.

Panel A	Drop Pre-COVID-19			Drop COVID-19		
	10%	15%	20%	10%	15%	20%
(C)AR	(n=194)	(n=123)	(n=75)	(n=185)	(n=127)	(n=78)
Day 1	-0.62%	-0.78%	-0.09%	-0.86%	-1.99%	-1.46%
	(-1.7975)	(-1.4594)	(-0.0973)	(-1.3139)	(-2.0192)	(-0.8968)
	[0.433]	[0.463]	[0.507]	[0.422]	[0.402]	[0.410]
Day 2	-0.05%	0.01%	1.06%	0.05%	-1.52%	-0.62%
	(-0.1573)	(1.5763)	(1.5726)	(0.1024)	(-2.3303)	(-0.9049)
	[0.515]	[0.569]	[0.587]	[0.465]	[0.402]	[0.474]
Day 3	0.40%	-0.15%	-0.08%	-0.39%	-1.54%	-0.05%
	(1.2839)	(-0.03439)	(-0.1720)	(-0.7468)	(-1.9636)	(-0.0482)
	[0.531]	[0.520]	[0.480]	[0.432]	[0.417]	[0.449]
Day 1-3	-0.27%	-0.12%	0.89%	-1.21%	-5.05%	-2.13%
	(-0.4626)	(-0.1359)	(0.7271)	(-1.1220)	(-2.6688)	(-0.8798)
	[0.463]	[0.528]	[0.547]	[0.427]	[0.377]	[0.410]
Day 4-20	-6.40%	0.79%	0.02%	-4.32%	-20.59%	-10.64%
	(-2.7138)	(0.5377)	(0.0106)	(-1.3196)	(-2.5717)	(-1.4740)
	[0.438]	[0.488]	[0.493]	[0.416]	[0.409]	[0.462]
Day 1-20	-6.67%	0.66%	0.91%	-5.53%	-25.64%	-12.77%
	(-2.5953)	(0.4434)	(0.4339)	(-1.4607)	(-2.7278)	(-1.5417)
	[0.448]	[0.512]	[0.520]	[0.438]	[0.409]	[0.449]

* Indicates that mean is significantly higher than 0 at the 0.05 level.
** Indicates that proportion is significantly higher than 0.50 at the 0.05 level

Panel B	Rise Pre-COVID-19			Rise COVID-19		
(C)AR	10% (n=172)	15% (n=89)	20% (n=48)	10% (n=222)	15% (n=184)	20% (n=121)
Day 1	0.10%	-0.47%	-0.61%	-0.71%	-0.64%	-0.51%
	(0.2894)	(-0.8355)	(-0.6464)	(-1.2658)	(-0.8281)	(-0.4540)
	[0.535]	[0.551]	[0.542]	[0.581]**	[0.576]**	[0.587]
Day 2	-0.05%	-0.39%	-0.63%	-0.43%	-1.51%*	-1.46%
	(-0.1630)	(-0.7924)	(-1.0001)	(-1.1849)	(-2.4501)	(-1.5423)
	[0.564]	[0.584]	[0.625]**	[0.572]**	[0.625]**	[0.612]**
Day 3	0.07%	0.13%	0.05%	-0.20%	-0.90%	-1.31%*
	(0.2879)	(0.4638)	(0.1639)	(-0.4759)	(-1.9478)	(-1.8173)
	[0.535]	[0.494]	[0.563]	[0.550]	[0.554]	[0.579]**
Day 1-3	0.12%	-0.72%	-1.18%	-1.34%	-3.05%*	-3.28%*
	(0.2444)	(-1.0082)	(-1.0381)	(-1.4362)	(-2.3428)	(-1.8963)
	[0.558]	[0.607]**	[0.583]	[0.581]**	[0.592]**	[0.587]**
Day 4-20	-0.97%	-0.40%	1.38%	-10.5%*	-11.15%*	-10.82%
	(-0.9398)	(-0.2491)	(0.6760)	(-3.0668)	(-2.2377)	(-1.6023)
	[0.477]	[0.494]	[0.4375]	[0.635]**	[0.565]	[0.579]**
Day 1-20	-0.84%	-1.12%	0.20%	-11.84%*	-14.19%*	-14.11%*
	(-0.7588)	(-0.6422)	(0.0811)	(-2.9568)	(-2.4477)	(-1.8135)
	[0.483]	[0.551]	[0.479]	[0.658]**	[0.587]**	[0.596]**

* Indicates that mean is significantly lower than 0 at the 0.05 level.
** Indicates that proportion is significantly higher than 0.50 at the 0.05 level

The cumulative abnormal return after the large drop during the COVID-19 pandemic shows a continuation of the drop and thus an underreaction. This contradicts the findings of Caporale and Plastun (2019). They found that the frequency of overreactions is informative about crises, a sharp increase in the number of overreactions is associated with a crisis period. Another contradiction with the literature is the combination of Figures 5 and 6, the cumulative abnormal returns after both the large one-day drop and rise during the COVID-19 pandemic stay negative. However, the Uncertain Information Hypotheses developed by Brown et al. (1988) suggest that stocks will eventually increase after both favourable and unfavourable surprising news.

Figure 5 Cumulative Abnormal Returns After a Large One-Day Price Rise During the COVID-19 Pandemic

This figure shows the cumulative abnormal returns after a one-day price rise of 10, 15 and 20 percent during the COVID-19 pandemic.

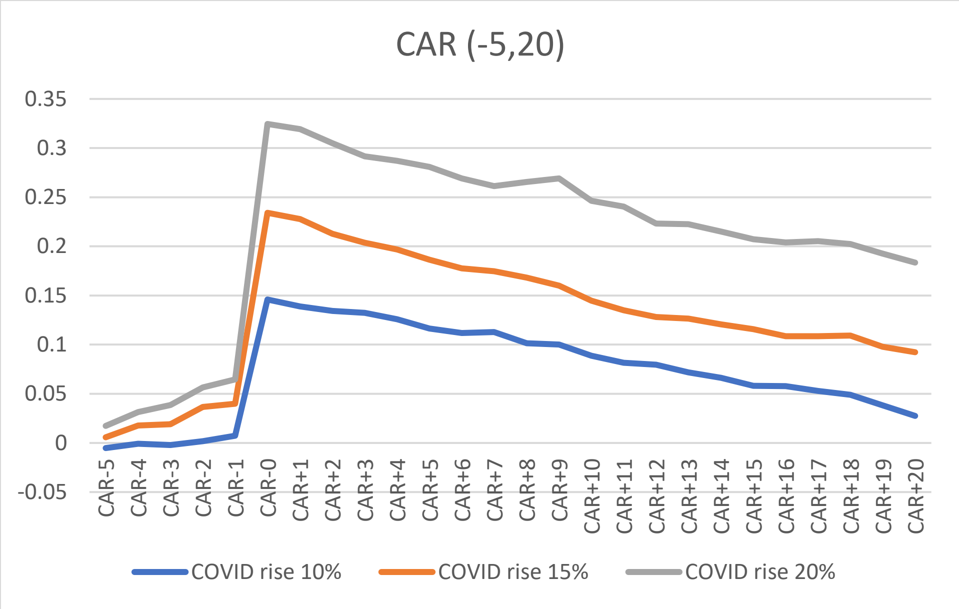
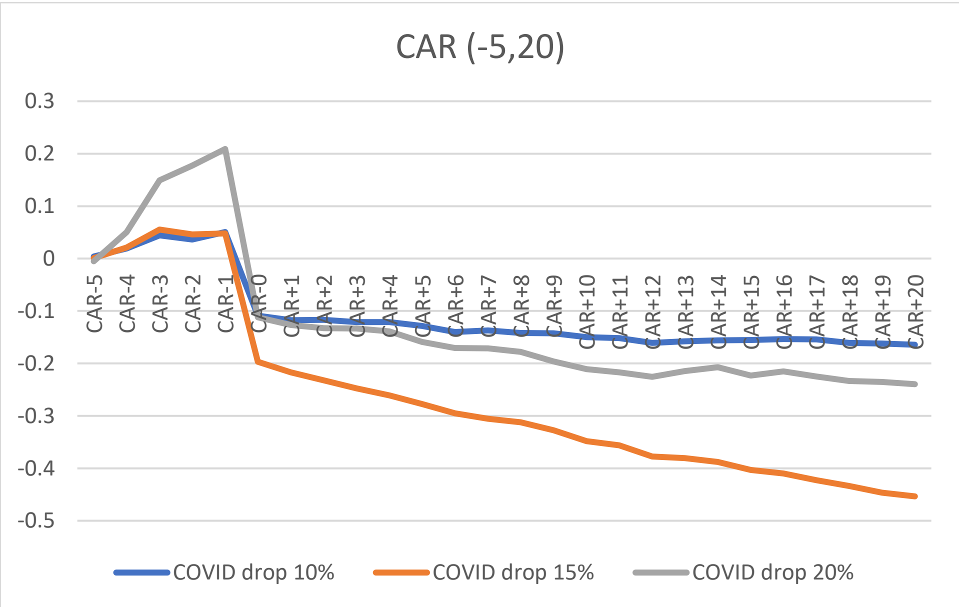


Figure 6 Cumulative Abnormal Returns After a Large One-Day Price Drop During the COVID-19 Pandemic

This figure shows the cumulative abnormal returns after a one-day price drop of 10, 15 and 20 percent during the COVID-19 pandemic.



5.2 Difference in cumulative abnormal return after a large one-day price movement before and during the COVID-19 pandemic

Plastun et al. (2021) have found that financial markets can evolve during periods of crisis. To find out if the COVID-19 pandemic has had influence on the behaviour of the market with respect to reaction of the stock return after a large one-day price movement, a Two-Tailed, Two-Sample t-Test has been run multiple times. The results of these Two-Tailed, Two-Sample t-Test can be seen in Table 6.

Table 6 Results Of the Two-Tailed, Two-Sample t-Test Of the Difference Of the (Cumulative) Abnormal Returns Following Large One-Day Price Movements Before And During the COVID-19 Pandemic

Difference between the mean (cumulative) abnormal returns before and during the COVID-19 pandemic are presented. Day 0 is the date of the large price movement. Difference is calculated by subtracting the CAR before the COVID-19 pandemic from the CAR during the COVID-19 pandemic. T-values of the Two-Tailed, Two Sample t-Test can be found in the parentheses

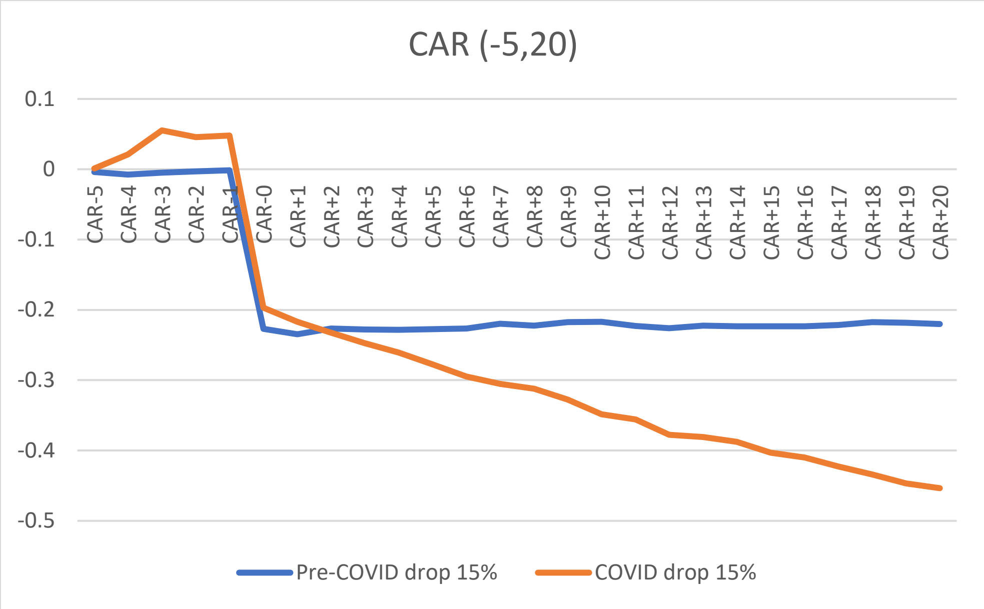
	Drop			Rise		
(C)AR	10%	15%	20%	10%	15%	20%
Day 1	-0.25%	-1.21%	-1.37%	-0.82%	-0.17%	0.10%
	(-0.3330)	(-1.0792)	(-0.7248)	(-1.2206)	(-0.1774)	(0.0661)
Day 2	0.10%	-2.32%	-1.68%	-0.39%	-1.12%	-0.84%
	(0.1722)	(-2.8062)	(-1.7488)	(-0.8228)	(-1.4207)	(-0.7342)
Day 3	-0.79%	-1.39%	0.03%	-0.27%	-1.04%	-1.36%
	(-1.2975)	(-1.5583)	(0.0254)	(-0.5556)	(-1.8978)	(-1.7316)
Day 1-3	-0.94%	-4.93%*	-3.02%	-1.47%	-2.33%	-2.10%
	(-0.7711)	(-2.3563)	(-1.1128)	(-1.3804)	(-1.5665)	(-1.0136)
Day 4-20	2.08%	-21.38%*	-10.66%	-9.54%*	-10.74%*	-12.21%
	(0.3035)	(-2.6264)	(-1.4222)	(-2.6661)	(-2.0515)	(-1.7294)
Day 1-20	1.14%	-26.30%*	-13.68%	-11.00%*	-13.07%*	-14.31%
	(0.2483)	(-2.7636)	(-1.6010)	(-2.6456)	(-2.1575)	(-1.7537)

* Indicates that difference is significantly different from 0 at the 0.05 level

In Table 6, it can be seen that the difference between the cumulative abnormal returns following a large one-day drop during the COVID-19 pandemic and the cumulative abnormal returns following a large one-day drop before the COVID-19 pandemic is only significantly different from 0 at the 15% trigger. In Figure 7 it can also be seen that the difference between the CAR before the COVID-19 pandemic and the CAR during the COVID-19 pandemic is quite big. However, for the other triggers the difference is not big enough to call it significantly different from 0. Therefore, it can be concluded that Hypothesis 6 – *The cumulative abnormal returns in the short-run following large one-day price drops during the COVID-19 pandemic are significantly different from the cumulative abnormal returns in the short-run following large one-day price drops before the COVID-19 pandemic* – can be rejected.

Figure 7 Cumulative Abnormal Returns Following a Large One-Day Drop (>15%) Before And During the COVID-19 Pandemic

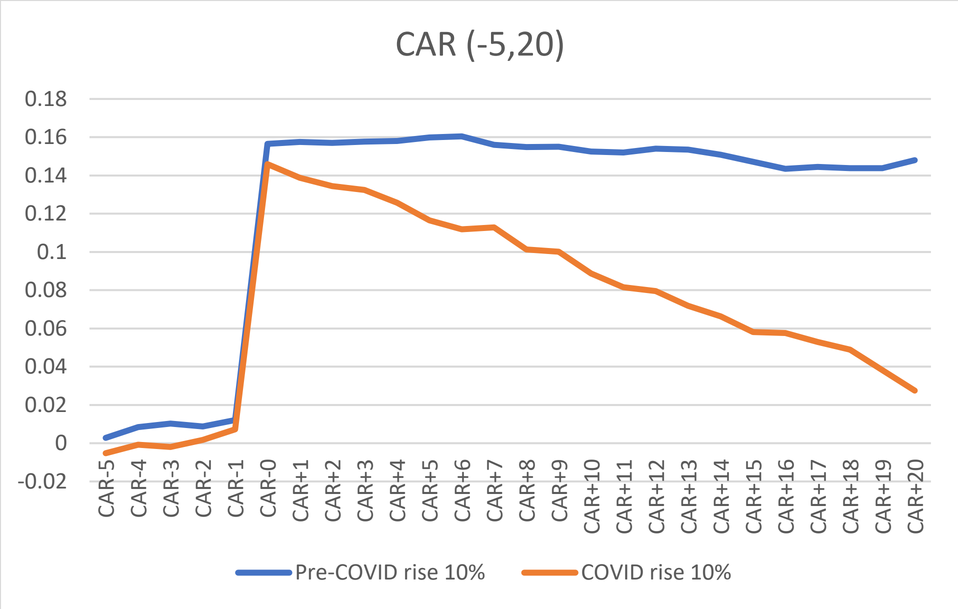
This figure shows the cumulative abnormal returns after a one-day price drop of 15 percent before and during the COVID-19 pandemic.



The difference between the cumulative abnormal returns following a large one-day rise during the COVID-19 pandemic and the cumulative abnormal returns following a large one-day rise before the COVID-19 pandemic are significantly different from 0 at the 10 and 15 percent trigger during the 4-20 and 1-20 trading days period, as shown in Table 6. Despite the fact that the differences are bigger during the 4-20 and 1-20 trading days period for the 20 percent trigger compared to the other triggers, it is not significantly different from 0. The reason for this is probably the number of events during the COVID-19 pandemic which is only 48 compared to 89 for the 15 percent trigger and 172 for the 10 percent trigger. The difference in pre-pandemic and pandemic CAR for the 10% trigger is also clearly visible in Figure 8. Taking all this information in consideration, it can be concluded that Hypothesis 5 – *The cumulative abnormal returns in the short-run following large one-day price rises during the COVID-19 pandemic are significantly different from the cumulative abnormal returns in the short-run following large one-day price rises before the COVID-19 pandemic* – can be accepted.

Figure 8 Cumulative Abnormal Returns Following a Large One-Day Rise (>10%) Before And During the COVID-19 Pandemic

This figure shows the cumulative abnormal returns after a one-day price rise of 10 percent before and during the COVID-19 pandemic.



5.3 Regression model

Multiple OLS regression analyses have been made. The results for the 10% rise and 10% drop dataset can be found in Tables 7 and 8, respectively.[5] The regressions had multiple (cumulative) abnormal returns as dependent variable. All these (cumulative) abnormal returns were reversals after the large one-day rise/drop. Therefore, all (cumulative) abnormal returns in Table 7 are negative and all (cumulative) abnormal returns in Table 8 are positive.

The variables Worst and Best in Table 7, explain the effect of being part of the worst or best performing industries during the COVID-19 pandemic on the (cumulative) abnormal return. It was expected that the reversal effect after a large one-day rise would be bigger for worst performing industries and smaller for best performing industries. It can be seen that the 'Worst' variable is in three of the six regressions negative and in three of the six regressions positive, so this variable does not show a clear direction. The 'Best' variable is in most regressions negative while it was expected to be positive so that the reversal would be smaller. Also the effect of the two variables on the (cumulative) abnormal return is quite small, since it is a dummy it can only be multiplied with 0 or 1. Furthermore, shows Table 7 that in none of the regressions the variables Worst and Best are significant. This means that being part of the worst or best performing industries during the COVID-19 pandemic has no effect on the (cumulative) abnormal returns after a large one-day rise. Therefore it can be concluded that Hypothesis 7 – *The reversal effect in the short-run following a large one-day price rise will be*

[5] The results for the 15 and 20 percent triggers can be found in the Appendix

significantly smaller for stocks that belong to the best performing industries during the COVID-19 pandemic – and Hypothesis 9 – *The reversal effect in the short-run following a large one-day price rise will be significantly bigger for stocks that belong to the worst performing industries during the COVID-19 pandemic* – can be rejected.

Table 7 OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Rise Of At Least 10% During the COVID-19 Pandemic as dependent variable.

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day rise of at least 10% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Rise 10%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	-0.1003	0.0576	0.0113*	-0.0106*	-0.0016	0.0055	-0.0146	1.15	0.1314
(n=126)	(-0.84)	(0.34)	(1.98)	(-2.18)	(-1.55)	(0.53)	(-1.07)		
AR2	0.1343*	0.0387	-0.006	0.004	-0.0013*	-0.0054	0.0022	1.34	0.0799
(n=92)	(2.06)	(0.48)	(-1.69)	(1.19)	(-2.26)	(-0.47)	(0.18)		
AR3	-0.1976*	0.2562*	0.0078*	-0.0041	0.0007	0.0029	0.0026	1.22	0.2461
(n=117)	(-2.35)	(2.21)	(2.19)	(-1.78)	(1.60)	(0.39)	(0.39)		
CAR3	-0.317	0.4434	0.0221	-0.0172	-0.0014	0.0028	-0.0283	1.2	0.1548
(n=127)	(-1.33)	(1.27)	(1.75)	(-1.97)	(-1.38)	(0.14)	(-1.50)		
CAR20	-1.8755	2.8589	0.0839	-0.0501	0.0071	-0.0966	-0.1377	0.85	0.1398
(n=143)	(-1.64)	(1.48)	(1.48)	(-1.33)	(1.23)	(-0.88)	(-1.60)		
CAR420	-1.896	2.4898	0.0795	-0.044	0.0103*	-0.0879	-0.1122	1.49	0.1571
(n=137)	(-1.96)	(1.58)	(1.72)	(-1.47)	(2.00)	(-0.86)	(-1.64)		

* Indicates that difference is significantly different from 0 at the 0.05 level

In Table 8 it is shown that the variable 'Worst' is statistically significant for one of the regressions (the regression with the abnormal return of the 2nd day after the event day as dependent variable). The variable has a negative effect on the abnormal return, this means that being part of the worst industry during the COVID-19 pandemic will make the reversal effect after a large one-day drop smaller, this is in line with what was expected. However, for none of the other regressions are the variables 'Worst' and 'Best' significant. Also it can be seen that for most of the regressions the 'Worst' variable is positive, while the opposite was expected. For most regressions the 'Best' variable is positive and this is in line with what was expected. However, the effect of both dummy variables is compared to the other variables and the constant term relatively small. Therefore it can be concluded that Hypothesis 8 – *The reversal effect in the short-run following a large one-day price drop will be significantly bigger for stocks that belong to the best performing industries during the COVID-19 pandemic* – and Hypothesis 10 – *The reversal effect in the short-run following a large one-day price drop will be significantly smaller for stocks that belong to the worst performing industries during the COVID-19 pandemic* – can be rejected.

Table 8 OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Drop Of At Least 10% during the COVID-19 Pandemic

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day drop of at least 10% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Drop 10%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	0.1907	-0.2556	-0.0032	-0.0063	-0.0008	0.0264	0.0048	0.58	0.1847
(n=77)	(1.24)	(-1.62)	(-0.63)	(-0.76)	(-0.48)	(0.75)	(0.31)		
AR2	0.2965*	0.1548	-0.0141*	0.0069	-0.0008	-0.034*	-0.0145	1.98	0.1026
(n=82)	(2.88)	(1.21)	(-2.50)	(1.16)	(-0.79)	(-2.63)	(-0.98)		
AR3	0.2664*	0.0162	-0.0094*	-0.0006	-0.0005	-0.01	0.0218	1.81	0.1194
(n=78)	(2.51)	(0.052)	(-2.57)	(-0.15)	(-0.59)	(-0.90)	(1.39)		
CAR3	0.3588*	-0.2575	-0.0069	-0.0116	-0.0002	0.0347	0.0039	1.94	0.2067
(n=79)	(2.22)	(-1.13)	(-0.92)	(-1.33)	(-0.16)	(1.18)	(0.17)		
CAR20	0.3687	-0.2932	-0.0234	0.0149	0.0009	0.1102	0.0404	1.5	0.113
(n=76)	(0.99)	(-0.74)	(-1.55)	(1.66)	(0.29	(1.41)	(0.79)		
CAR420	-0.4295	-0.1415	-0.0018	0.0294*	0.0063*	-0.0093	0.0451	2.19	0.1416
(n=72)	(-0.96)	(-0.49)	(-0.11)	(2.75)	(2.30)	(-0.10)	(0.82)		

* Indicates that difference is significantly different from 0 at the 0.05 level

6 Conclusion

This paper examined the difference in the short-term reaction of stock returns in the U.S. stock market after a large one-day price movement before and during the COVID-19 pandemic. This has been done by investigating the cumulative abnormal returns of NYSE stocks after a large one-day price movement of at least 10, 15 and 20 percent, for both rises and drops. Two periods have been examined, before the COVID-19 pandemic from November 2018 to October 2019 and during the COVID-19 pandemic from April 2020 to March 2021.

This paper concluded that the short-term reaction of stock returns in the U.S. stock market after a large one-day drop has not changed during the COVID-19 pandemic compared to the period before the pandemic. In both periods the cumulative abnormal return was negative. In other words, on average the stocks continued to drop after the large one-day drop. On the other hand, this paper found that the short-term reaction of stock returns in the U.S. stock market after a large one-day rise has changed significantly during the COVID-19 pandemic compared to the period before the pandemic. Before the COVID-19 pandemic, there was no significant short-term reaction after a large one-day rise. However, during the COVID-19 pandemic, a significant reversal effect was found. For stocks that increased at least 10% in one day, the 20-trading days cumulative abnormal return was on average 11.00%. Belonging as a company to the best/worst performing industries during the COVID-19 pandemic had no significant effect on the cumulative abnormal return after a large one-day price movement. The main conclusion of this paper is that only a difference in the short-term reaction of stock returns in the U.S. stock market after a large one-day price rise can be found when comparing the period before and during the COVID-19 pandemic. Before the pandemic no reversal effect was found, whereas during the pandemic a significant reversal effect was found. For stocks that had a large one-day price drop no significant difference is found when comparing the period before and during the COVID-19 pandemic. The reaction of the stocks in both periods is a continuation of initial large one-day drop.

The limitations of this paper were the relatively short periods of 1 year to find large one-day price movements. Due the fact that the COVID-19 pandemic started not so long ago, it was not possible to make the period during the COVID-19 pandemic any longer. Additionally, this paper has not looked at the bid-ask spread but only at the closing price. The intention of this paper was to look purely at the difference in reaction of stock returns after a large one-day price movement and not to find a profitable investment strategy. Future research could build on the results of this paper and investigate if there were possibilities of a profitable investment strategy after large one-day price movements during the COVID-19 pandemic. Further, the calculation of the abnormal returns were limited to the assumptions of the market model. In future research different calculations for the abnormal returns could be used to see if the results are still the same.

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Appendix

Table A OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Drop Of At Least 15% during the COVID-19 Pandemic

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day drop of at least 15% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Drop 15%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	0.4285	-0.1932	-0.003	-0.0151	-0.0027	0.0262	-0.0197	0.84	0.2459
(n=50)	(1.84)	(-0.25)	(-0.65)	(-1.18)	(-1.82)	(0.71)	(-1.17)		
AR2	-0.0132	0.0871	0.0048	-0.0014	-0.0005	0.013	0.0039	0.47	0.0615
(n=50)	(-0.14)	(1.40)	(0.95)	(-0.36)	(-0.61)	(0.60)	(0.22)		
AR3	0.2327*	0.0279	-0.01*	0.0009	0.0006	-0.0309	-0.0011	1.56	0.1891
(n=50)	(2.95)	(0.88)	(-2.55)	(0.30)	(0.78)	(-1.84)	(-0.08)		
CAR3	0.2605	-0.0692	0.0031	-0.0156	-0.0012	0.0235	0.038	1.16	0.2456
(n=47)	(1.62)	(-0.42)	(0.53)	(-1.52)	(-0.64)	(0.65)	(1.46)		
CAR20	0.6428	-0.0232	-0.0149	-0.0031	-0.0029	-0.0703	-0.0432	0.25	0.0338
(n=50)	(1.36)	(-0.10)	(-0.62)	(-0.19)	(-0.66)	(-0.79)	(-0.55)		
CAR420	-0.493	-0.0021	0.0098	0.0217	0.0048	-0.0866	0.0091	0.52	0.0532
(n=50)	(-0.66)	(0.01)	(0.36)	(1.02)	(0.88)	(-1.25)	(0.13)		

* Indicates that difference is significantly different from 0 at the 0.05 level

Table B OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Rise Of At Least 15% during the COVID-19 Pandemic

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day rise of at least 15% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Rise 15%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	-0.0886	0.0663	0.0171*	-0.0178*	-0.0033*	-0.001	0.0124	2.58	0.2083
(n=100)	(-0.58)	(0.40)	(2.52)	(-3.70)	(-2.11)	(-0.07)	(0.71)		
AR2	-0.0552	-0.0441	0.0082	-0.0086*	-0.0012	0.0059	-0.0055	1.6	0.0555
(n=106)	(-0.44)	(-0.19)	(1.56)	(-2.07)	(-0.97)	(0.31)	(0.30)		
AR3	-0.2599*	0.2487*	0.0112	-0.0067*	0.0013	0.0095	-0.0101	2.66	0.2567
(n=94)	(-2.41)	(2.17)	(1.89)	(-2.22)	(1.47)	(0.87)	(-0.80)		
CAR3	-0.4107	0.2126	0.0358*	-0.0286*	-0.0025	0.0033	-0.0145	2.23	0.1082
(n=102)	(-1.36)	(0.46)	(2.49)	(-3.20)	(-1.17)	(0.12)	(-0.43)		
CAR20	-3.1758*	3.5817	0.167*	-0.1119*	0.0047	0.0267	0.1489	1.33	0.2344
(n=102)	(-2.04)	(1.81)	(2.18)	(-2.52)	(0.43)	(0.16)	(1.15)		
CAR420	-2.9923*	4.0044*	0.1444*	-0.0927*	0.0044	-0.0656	0.1314	1.4	0.2946
(n=98)	(-2.22)	(2.12)	(2.19)	(-2.39)	(0.39)	(-0.35)	(1.16)		

* Indicates that difference is significantly different from 0 at the 0.05 level

Table C OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Drop Of At Least 20% during the COVID-19 Pandemic

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day drop of at least 20% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Drop 20%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	0.5393*	0.0642	-0.0016	-0.0188	-0.0038	0.0288	-0.0582	2.63	0.215
(n=32)	(2.10)	(0.58)	(-0.23)	(-1.34)	(-1.47)	(0.51)	(-1.74)		
AR2	0.1102	0.0573	-0.0038	0.0003	0.001	-0.031	-0.029	1.72	0.2149
(n=36)	(1.02)	(1.30)	(-0.76)	(0.12)	(0.83)	(-1.97)	(-2.21)		
AR3	0.5961*	0.0538	-0.0129	-0.014*	-0.0011	-0.0156	-0.0023	4.19	0.4824
(n=34	(3.70)	(0.73)	(-1.85)	(-3.23)	(-0.86)	(-0.49)	(-0.10)		
CAR3	0.5941*	-0.0695	-0.0033	-0.0255*	-0.0011	-0.0114	-0.0551	2.39	0.3568
(n=32)	(2.13)	(-0.25)	(-0.24)	(-3.56)	(-0.39)	(-0.29)	(-1.17)		
CAR20	0.7234	-0.0797	-0.0186	-0.0155	0.004	-0.0389	-0.0975	1.08	0.1886
(n=35)	(1.28)	(-0.24)	(-0.64)	(-0.81)	(0.77)	(-0.35)	(-0.97)		
CAR420	-0.927	0.0379	0.0235	0.0185	0.0125	-0.0203	-0.0317	1.06	0.1186
(n=36)	(1.10)	(0.26)	(0.71)	(1.23)	(2.05)	(-0.28)	(-0.43)		

* Indicates that difference is significantly different from 0 at the 0.05 level

Table D OLS Regression Analyses For Multiple (Cumulative) Abnormal Returns After a One-Day Rise Of At Least 20% during the COVID-19 Pandemic

This table shows the results of the regression analyses. The (cumulative) abnormal returns after a large one-day rise of at least 20% during the COVID-19 pandemic are regressed against the event day abnormal return (AR0), a size variable based on the market cap (SIZE), the log of the trading volume on the event day, the volatility index and two dummy variables were Worst/Best is 1 if the firm of the stock is operating in the worst/best performing industries during the COVID-19 pandemic. T-values can be found in the paratheses.

COVID Rise 20%	**Intercept**	**AR0**	**SIZE**	**TV**	**VIX**	**Worst**	**Best**	**F-Value**	**R-Squared**
AR1	0.0755	-0.0929	0.0083	-0.0176*	-0.0011	0.0028	0.0152	1.25	0.1472
(n=69)	(0.43)	(-0.71)	(1.12)	(-2.65)	(-0.69)	(0.14)	(0.61)		
AR2	0.0012	-0.1935	0.0077	-0.01	-0.001	0.0398	0.024	1.49	0.0999
(n=68)	(0.01)	(-0.68)	(1.02)	(-1.95)	(-0.63)	(1.43)	(0.99)		
AR3	-0.2371	0.2193	0.0134*	-0.0119*	0.0015	0.0092	-0.0096	1.48	0.1437
(n=65)	(-1.50)	(1.62)	(2.10)	(-2.08)	(1.32)	(0.51)	(-0.39)		
CAR3	-0.2142	-0.1957	0.0267	-0.0244	-0.0017	0.0331	0.0112	1.69	0.0718
(n=69)	(-0.65)	(-0.34)	(2.27	(-2.51)	(-0.65)	(0.74)	(0.22)		
CAR20	-3.3792	2.6207	0.125*	-0.048	0.0086	0.2204	0.144	1.56	0.1456
(n=70)	(-1.77)	(1.21)	(2.02)	(-1.56)	(1.02)	(1.01)	(0.91)		
CAR420	-2.8146	3.2261	0.0715	-0.0255	0.0135	0.09	0.1942	1.59	0.1813
(n=50)	(-1.59)	(1.46)	(1.45)	(-0.83)	(1.66)	(0.45)	(1.33)		

* Indicates that difference is significantly different from 0 at the 0.05 level