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MSc Economics & Business
Specialization Financial Economics

This time it's different.

Exploring the short-term overreaction in the US stock market during COVID-19.

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PREFACE AND ACKNOWLEDGEMENTS

Hereby I would like to thank my mom Chandra Khedoe, my dad Soegriem Khedoe and my partner Nick Bakker for their unconditional love, motivation, and support. I couldn't have done this without you. I would also like to thank study advisor Ms. M. Hemmes for giving me guidance in this process.

ABSTRACT

This study examines if regular investors could benefit from the overreaction hypothesis on the S&P500 during COVID-19. The results reveal a lack of clear evidence supporting the overreaction hypothesis. Nevertheless, a short-term momentum strategy emerges as a potential beneficial approach for investors. Exploring factors such as firm size and investor sentiment yield unexpected results. For instance, smaller firms do not exhibit higher returns and there is a positive relation between the investor sentiment and cumulative abnormal returns. These finding indicate that conventional understanding of how investors and stock are supposed to behave may not hold true in times of crisis.

Keywords: Overreaction hypothesis, Financial market, Growth stock, Value stock, Investment strategy, COVID-19.

JEL Classification: G41

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1. Introduction

Financial bubbles, and their downfalls leave their marks in the economy. Researchers Brunnermeier and Oehmke (2013) specify two stages of a financial bubble: the run up phase and the crisis phase. In the run up phase a financial bubble arises because the underlying value is lower than the investor sentiment. In the beginning this is justified for example by innovation. Researcher Robert Shiller (2000) emphasizes how the willingness of investors to pay a premium for the possible future growth opportunities led to the overvaluation of the dot.com company. Furthermore, researchers Frehen, Gootzmann and Rouwenhorst (2013) find that innovation is a key driver of bubble expectations. In this run up phase there are distortion incentives which investors try to monetize with all associated risk. Abreu and Brunnermeier (2003) divide the investors into 2 categories: The irrational investors who are uninformed and drive the prices up and the rational investors who try to ride the bubble to gain an abnormal return. Consequently, when the stock gains momentum the innovation explanation doesn't stand ground. After the gradual buildup of the price, a trigger heralds the crisis phase. In the crisis phase the stock that experienced irrational growth will have a sharp fall in price (Pastor and Veronesi, 2009).

Besides financial bubbles, there are many other reasons why abnormal returns exist. Researchers Conrad and Kaul (1993) point out the importance of the bid- ask bounce. Zarowin (1990) attributes abnormal returns to the size effect of firms and Graham (1973) found significant evidence for the price earnings effect with research on the Dow Jones Industrials. Researcher Reignanum (1991) stresses that there could be other unknown factors that cause abnormal returns. Moreover, he argues that the price earnings ratio and small firm effect subsume each other. Researchers Barber and Odean (2000) have shed light on multiple behavioral biases and how these influence investors and investor sentiment when trading. These biases include: the overconfidence bias, herding behavior, loss aversion and the disposition effect. In chapter 2 these will be discussed. These biases can all be linked to the renowned hypothesis of overreaction which is formed by de Bondt and Thaler (1985).

The overreaction hypothesis states that investors tend to react excessively, and therefore irrationally, when new information becomes public. After investors processed this news, they alter their investment in the same excessive way. Researchers de Bondt and Thaler (1985) conclude that there will be a price reversal where current 'winners' will become 'losers' and vice versa. Winners are stocks that have positive returns and losers negative returns. The overreaction hypothesis contradicts the efficient market hypothesis (EMH) which states that markets are efficient and that stock prices reflect new information quickly (Fama, 1960).

Picolli and Chaudury (2018) confirm the existence of the overreaction hypothesis in their research towards the US stock market. They capture the investor sentiment with the Baker and Wugler sentiment list and find that there is overreaction on individual stocks. Besides, the overreaction is higher when there is low investor sentiment. This is in line with the research of Yu and Yuan (2011). They find a positive tradeoff in times of low investor sentiment, while the tradeoff in high investor sentiment periods remains absent. Chan (1988) states that losers outperform winners because of the short-term overreaction. Because this is a known phenomenon investors can leverage the situation by using a contrarian investment strategy.

There is already a large literature based on the overreaction hypothesis, but the event of Covid-19 has not been broadly examined yet. The Covid-19 pandemic was an unforeseen crisis which impacted people's health and had tremendous effect on the economy. The goal of this paper is to examine whether regular investors can benefit from the overreaction hypothesis on the S&P500, in times of a crisis. This will be done by using an event study and a multivariate regression.

This paper will add to the already existing literature by examining a new event (Covid-19) and by investigating the impact of the difference of a growth and value stock. The practical implication of this research is the possibility to form an investment strategy based on an unexpected price reversal. The social implication is that it can help other individuals and investors to better understand the market. Additionally, it raises a healthy challenge against the efficient market hypothesis which can lead to fruitful discussions and a more realistic framework that describes the market.

2. Literature review:

In this chapter relevant literature will be discussed. First the price reversal theory and elements which may cause it, will be discussed based on existing literature. Second the impact of COVID-19 on the stock market will be examined and lastly the hypotheses are presented.

2.1 Price reversal theory

The efficient market hypothesis has been a corner stone in the economic theory. The EMH states that stock prices reflect their fair value because the prices quickly adjust to all available public information. Therefore, making a gain by buying and selling stocks shouldn't be possible (Fama and French, 1960). However, there is evidence against the efficient market hypothesis since stock prices can have an unforeseen direction change and deviate from their fair value. This direction can change upwards or downwards and is often referred to as the price reversal theory (de Bondt and Thaler, 1985).

The price reversal theory states that stock which are now well performing are more likely to fall in price in the future and vice versa. These price reversals can either be long-term or the short term. Long term price reversals take several months or years to unfold while short term reversals happen within days or weeks (de Bondt and Thaler, 1985).
There have been many studies conducted to the determinants of the price reversal theory and many possible explanations have been found. One of these determinants is the seasonal effect, where prices behave in a certain way in specific period. Other determinants are firm characteristics or behavioral biases such as the overreaction theory (De Bondt and Thaler, 1985).

The price reversal effect leads to opportunities for investors. Once the price reversal anomaly in the market is spot, investors can use a trading strategy to generate profits. Besides, it gives investors a new angle which shows them the importance of rational behavior instead of panic buying/ selling.

2.1.1 Explanations behind the price reversal theory

Many researchers have examined what could be the potential cause of the price reversal phenomenon. Researchers Keim and Stambaugh (1985); French (1980); Cross (1973) and Gibbons and Hess (1981) examined the relation of the price changes distribution on Mondays and Fridays. They concluded that this price reversal might be due to the weekend effect. This weekend effect, or negative Monday effect regards the observation that there is a non-random movement in the stock prices (Cross, 1973). This movement shows that the average returns on Monday are negative when comparing the close price on Monday to the close price on the previous Friday (Keim and Stambaugh, 1985).

Another possible explanation for the price reversal is the size effect. Zarowin (1990) concluded that outperformance might be due to the size effect. The size effect refers to the observation that losers are smaller sized firms than winners. Researcher Banz (1981) states that smaller firms have higher risk adjusted returns than larger firms and specify that this is evidence that the capital asset pricing model (CAPM) is not specified correctly. He also signals that the size effect should be used carefully since it could be that size is a proxy for an unknown variable which is highly correlated with size instead of the true cause.

Conrad and Kaul (1993) added the bid-ask spread to the possibility list for abnormal returns. They imply that a wider bid-ask spread lead to higher transaction cost which reduces the abnormal returns. Researchers Vermaelen and Verstringe (1986) explain that the price reversal might be there due to the time varying equilibrium returns. This means that the relationship between the asset price and underlying value can differ over time, which makes it difficult for investors to estimate the asset price since not all information is reflected in the fundamentals.
Bernestein (1985) comes with a different angle and states that investors might go for simplicity and just extrapolate the historical data. And by doing so they ignore the reversion to the mean principle, where prices converge back to an average. According to de Long, Shleifer, Summers and Waldman (1987) this could be the case, but it is very unlikely that rational arbitrageurs can spot this short-term anomaly and act on it.

2.2 Overreaction hypothesis

Another explanation for the price reversal theory is the overreaction hypothesis. According to multiple researchers such as de Bondt and Thaler (1985); Mun et al. (2000) and Clare and Thomas (1995), the overreaction hypothesis states that individuals tend to overreact to news. This leads to stock prices moving in one direction which is followed by a reversal in the opposite direction.

De Bondt and Thaler (1985) found evidence for the overreaction hypothesis. They examined the New York Stock Exchange (NYSE) from 1926 to 1982 and find that extreme movements in stock prices will be followed by subsequent price movements in the opposite direction. The more extreme the initial price movement is the greater the subsequent adjustment will be. De Bondt and Thaler (1985) conclude that now winners will become losers and vice versa. Winners being stocks that currently outperform the market and losers underperform the market. These winning and losing stocks will switch sides, due time. In addition to this they make two remarks, first that the overreaction hypothesis is asymmetrical. Loser portfolios outperform the market with 19.6% after 36 months, while winner portfolios perform 5% less than the market (de Bondt and Thaler, 1985).

There is a significant amount of evidence in support of the overreaction hypothesis. For example, researchers Ma, Tang, and Hassan (2005) examined the NYSE and the NASDAQ from January 1996 until December 1997. They concluded that for the NASDAQ there is strong evidence in favor of the overreaction hypothesis. There is a more pronounced effect for losers than for winners. However, for the NYSE they did not find significant evidence for the overreaction effect. It could be that the different sector composition of the exchanges causes this. The NYSE is known for many well-established and large cap companies, while the NASDAQ is known for technology and internet-based companies. Researchers Chopra, Lakonishok and Ritter (1992) build on the work of de Bondt and Thaler and studied the US market from 1926 until 1986. In this study they controlled for firm size and systematic risk and found that especially for smaller firms the overreaction was present. Beside they note that there might be a difference in the type of investors, individual traders often trade with stocks of smaller firms while institutions often trade with stocks of large companies. Researcher Stock (1990) applied the empirical study of de Bondt and Thaler (1985) to the German market over the period 1973-1989. His results are in line with de Bondt and Thaler since he found evidence of long-term investor overreaction. For the short-term he concludes that both winners and losers tend to continue their initial price movement. His findings are a violation of the weak form of market.

Researchers Bremer and Sweeney (1991) examined the US stock return from 1962 – 1986 and applied a 'trigger value'. They quantified their event days with an overreaction trigger as a 10% decrease in the stock price in one day. They find that there is evidence for the price reversal effect. A large negative daily return tends to be followed by a positive rebound in the next two days. Meaning that after a large decrease of the stock price, in the following 2 days there tends to be an unexpected recovery of this decrease. Evidence for long-term overreaction is found in other stock market such as, the Spanish market during 1967 – 1984 (Alonso and Rubio,1990). The Brazilian market during 1970-1989 (De Costa, 1994) and the UK market during 1950-1995 (Clare and Thomas, 1995).

However, some researchers have criticized the overreaction hypothesis and found evidence which is not in line with that of de Bondt and Thaler. Ball and Kothari (1989) show that when the annual returns are used to approach the betas, instead of cumulating single period monthly returns, there aren't any abnormal returns. Zarowin (1990) constructed a 3 year non overlapping portfolio over time period 1932- 1977, after controlling for risk, seasonality, and size he concluded that there is no significant evidence for the overreaction hypothesis. In his prior work, he showed that when controlling for size and risk on the US market in the period 1927-1985, if winners and losers are grouped, winners always outperform the losers.

Researchers Cox and Peterson (1994) and Arbel and Jaggi (1982) examined the US market and did not find significant results for the overreaction hypothesis. Larson and Madura (2003) find support for the overreaction hypothesis on the US market but only in the case of non-public announced events. Investors appear to react with excessive confidence to private information and underreact to public information. Researchers Atkins and Dyl (1990) examined the US stock market and found evidence that the stock market only overreacts to bad news.

Conrad and Kaul (1993) pointed out that using the approach of de Bondt and Thaler, with cumulate short-term returns can lead to an upward bias in each return period which is unrelated to the market's overreaction. Therefore, they used a buy and hold strategy which has the advantage that it minimizes transaction cost and reduces the bias in cumulative performance measures. They show that abnormal returns are due to a seasonal effect and that there is no evidence for the overreaction hypothesis. Nevertheless, other researchers controlled for the critiques of Conrad and Kaul and still found evidence in favor of the overreaction hypothesis. Researchers Mun, Vasconcellos and Kish (1999) remark that the estimate of portfolio performance is highly sensitive to the methods used for computing the (formation) period returns and the same goes for the estimations of the betas. To avoid these pitfalls, they applied a non-parametric rank-based regression and bootstrap simulation and conclude that for the German and French market the overreaction hypothesis is present.

2.2.1 Explanation determinants overreaction hypothesis

In the realm of behavioral finance scholars such as Kahnemant et al. (1992) and de Long et al. (1990) extensively examined the complexities of decision-making faced by investors. Despite the rational normative models, individuals often deviate from this due to behavioral biases. Beyond the realm of behavioral biases, firm and market characteristics are crucial to overreaction in the stock market, which will be explained below.

Behavioral biases:

Kahneman et al. (1972, 1974) established that individuals have an availability bias. Individuals tend to overweigh recent information of events and underweight information which is further in the past resulting in overreaction. Besides, individuals are using a rule of thumb to make decisions, which is known as the representative heuristic. Individuals tend to estimate the probability of a future event based on relatable experiences. This cognitive tendency introduces biases to their judgement. An extreme market movement has a low probability of occurring, for investors this elicits the emotion of surprise which leads to overweighing the incident (Griffen and Tversky, 1992; Meyer, Reisen and Schützwohl, 1997).

Mental accounting plays a role in why individuals are willing to sell winning stock so quickly and hold on to losers. Mental accounting refers to mentally using a different wallet for each purchase. The purchase of a stock is accompanied by a new mental account. Decision makers tend to apply a separation technique to these mental accounts and apply prospect theoretic rules to each account by ignoring possible interaction (Thaler and Shefrin, 1981). They therefore do not act rational and tend to overreact by selling too quickly. According to loss aversion, investors experience a larger decline in emotional well-being, utility, when faced with losses of a certain magnitude compared to the positive impact of equivalent gains. (Kahneman and

Tversky, 1992). This depicts how the reaction to losses, or more general negative news is amplified compared to good news.

The next behavioral bias is herding. In essence, when investors are herding, they suppress their own beliefs and mimic the financial trading activities of others (Chiang and Zheng, 2010). According to de Long et al. (1990) and Avery and Zemsky (1998) herding behavior can lead to price overreaction in the market since it causes prices to drift away from their fundamental value. This can be seen when the returns are compared to the market returns. The cross-sectional dispersion of the fluctuation from the returns should have been less than proportional with the market return (Christie and Huang, 1995).

According to Dreman (1982) investors can overreact by being too optimistic which drives the prices up and creates a bubble. Researchers Malmendier and Tate (2005) add that when investors are too optimistic, they overestimate the influence they have in a situation. The overconfidence bias explains that compared to others, people overestimate their ability by thinking they are better than the average and have a severe miscalibration on the accuracy of the information they have. Researchers Hirshleifer, Low and Tech (2012) stress that overconfident managers are more likely to invest in innovative investments. This is in line with the results of researchers Frehen, Gootzmann and Rouwenhorst (2013) who found that innovation is a key driver of bubble forming and therefore overreaction. Researchers Barber and Odean (2001) argue that due to the overconfidence bias, individual investors tend to trade too much, which diminishes any returns.

<u>Firm and market effects:</u>

The overreaction hypothesis seems to be influenced by seasonal effects. Researchers Chopra, Lakonishok and Ritter (1992) confirm that near the quarterly earnings announcements the overreaction is observable. Researchers Ma, Tang and Hassan (2005) confirm the end of the year effect or January effect, where market participants sell their losing stocks in December to harvest tax losses, and in January they buy back the same stock. Researchers Shefrin and Statman (1985) argue that the January effect flows from the disposition effect. Because investors tend to sell winners too quickly and hold on to losers too long, in December there is a combined effect of selling losing stocks due to the disposition and for a capital gain. However, researchers Conrad and Kaul (1993) find that the January effect explains the actual returns of an arbitrage portfolio and eliminates the overreaction.

Researcher Zarowin (1990) found in his research to the overreaction hypothesis on the US stock market a size effect. Losers that outperform winners are often smaller firms. In addition, Fama and French (1992) state that the first few months after a stock has had a price reversal the size effect is the strongest. Researcher Banz (1981) states in his research on the NYSE that smaller firms often have higher average returns than large firms. Researchers Jegadeesh and Titman (1993) found similar results when examining the AMEX and NYSE. They argue that losers outperform winners and observe that losers contain smaller market capitalization than winners. Researchers Chopra, Lankonishok and Ritter (1992) concluded the same and stated that the overreaction effect is strongest for small firms.

Researchers Amihud and Mendelson (1986) found that on the NYSE stocks with low liquidity tend to produce higher returns and experience a greater price reversal. Researchers Bremer and Sweeney (1991) and Cox and Peterson (1994) found similar results when they examined the US market and found that larger price reversals happen in less liquid places. Liquidity is a measurement which depicts how easy an asset can be bought or sold. The less liquid an asset is, the harder it is to trade in it.

Baker and Wurgler (2007) define investor sentiment as a subjective belief about future investment risks and cashflows. These believes influence the way investors make decisions (Chari, Hedge-Desai and Borde, 2017). Researchers Piccoli and Chaudury (2018) examined what effect investor sentiment has on the overreaction phenomenon and conclude that the overreaction is more pronounced in times of low sentiment. This is not in line with earlier work from Stambaugh et al. (2012) who find greater anomalies when investor sentiment is high. Researchers Praveen et al. (2020) examined the Pakistani market and argue that the overreaction is driven by investor sentiment which emerges from heuristics such as overconfidence. Researchers Chi, Zhuang and Song (2012) conclude that on the Chinese market investor sentiment has a big impact on the returns. Researcher Loang (2022) examines the impact of investor sentiment on overreaction before and during Covid-19. He concludes that before Covid-19 there is a correlation between the sentiment index and the stock returns, however in times of the pandemic this relation is insignificant except for losers in the NASDAQ. This indicates that in turbulent periods investors utilize the prices of the previous day as a benchmark for trades.

Researchers Vermaelen and Verstringe (1986) conducted a study akin to that of de Bondt and Thaler, contending that overreaction is a response of the market's reaction to the change in risk. The crux of the risk change effect is that individuals are overreacting based on how they assess the risk of a stock. Specifically, they propose that decreases in stock prices will lead to an increase in risk debt- equity (D/E) ratios. Building on this, researcher Chan (1988) elaborates that an increase in the D/E ratio will lead to a higher risk of the stock. Ben-David, Graham and Harvey (2013) argue overreaction phenomenon is higher in times of high leverage. In a broader context, a higher debt to equity ratio signifies higher leverage. According to Berk and DeMarzo (2017) elevated leverage results in higher idiosyncratic risk for stockholders. Consequently, this implies that the return on the stock will be lower.

Next to the D/E ratio, scholars such as Pilloff (1996) and Berk and Demarzo (2017) emphasize that the return on equity (ROE) is a profitability indicator, which illustrates the capability of a company to capitalize on investment opportunities. This implies that a higher return on equity will result in higher returns on the stock. Surprisingly, in current literature the ROE is not broadly covered as a potential contributor to the overreaction. It is therefore interesting to explore if a higher ROE will lead to higher returns in terms of the overreaction hypothesis.

Researchers Daniel and Titman (1997) conclude that investors overreact to performance of the stock. A value stock is a stock that has a strong current fundamental for the earnings power and book value. However, the price is currently undervalued because of overreaction of investors. The price is expected to rise in the future when the overreaction is corrected. Investing in value stocks is called the value strategy, while investing in growth stocks is a growth strategy. A growth stock is a stock that has growth potential on the long term. Consequently, the stock appears to be sensitive to news. The prices are higher than the intrinsic values and the value ratios are low. The growth strategy is based on the EMH, the current prices reflect all important information and therefore the stock is not overpriced, but signals it future growth potential (An, Cheh and Kim, 2017). Multiple researchers such as Basu (1983); Rosenberg Reid and Lanstein (1985); Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994) concluded that value stocks have on average a higher return than growth stocks. Fama and French (1992) point out that value strategies are fundamentally riskier than growth strategies. Therefor value stocks have on average higher returns, to compensate for this risk. Lakonishok, Shleifer and Vishny (1994) argue that a value premium arises because the market undervalues stocks in distress and overvalues growth stocks.

2.2.2 Implications of the overreaction hypothesis

The overreaction hypothesis suggests that potential opportunities arise for investors to profit from the market mispricing. Researchers Graham and Dodd (1934) emphasize that it is crucial to analyze fundamental metrics to determine whether there might be a mispricing,
A commonly used method is the contrarian investment strategy. With this strategy individuals try to capitalize the mispricing by buying underperforming assets and sell outperforming assets (Bouwman and Iverson, 1998; Chan,1988). Jegadeesh and Titman (1993) emphasize how the contrarian strategy is only suitable on the long term. Besides the contrarian strategy investors who can spot the market mispricing can use value investing to capitalize on the mispriced asset. Value investing is investing in a value or growth stock. Jegadeesh and Titman (1993) stress that momentum strategy can complement value investing. With the momentum strategy investors believe that current outperformers will keep outperforming and underperformers will keep underperforming. Jegadeesh and Titman (1993) prove this with their research on the NYSE and AMEX. Researchers Hong, Lim and Stein (2000) provide support for the momentum strategy with their finding that underreaction to bad news might be a reason why weak performing stock stay in the low performance zone. Rouwenhorst (1998) supports this strategy with his research to 12 European countries during the period 1980-1995.

Considering the literature discussed above, several firm characteristics influence the overreaction hypothesis, offering investors avenues to maximize their returns. In particular investors should consider the seasonal effect and anticipate on a price drop. The insight of researcher Zarowin (1990) suggest investors could benefit by incorporating stocks with smaller market capitalization into their contrarian strategy. Besides, based on the insights of Piccoli and Chaudury (2018) investors could act on periods with low sentiment where the overreaction is more present. Additionally, investors could conduct a back test on liquidity for the stock to see for a certain stock if a low liquidity leads to historical higher returns. Employing such an approach will help investors refine their strategies and make more informed decisions.

2.3 Covid-19 and the stock market

In December 2019, the virus Covid-19 broke out in China. The virus was highly contagious and within weeks it had spread over the world. In January 2020 the World Health Organization (WHO) declared that there was a public health emergency of international concern, and in March 2020 they labeled it as a pandemic (WHO,2020). Besides people's health, this pandemic struck the economy as well. Almost all countries had to take measures due to the pandemic. Measures consisted of lock downs in economic activities, the ban of travel to other countries and financial aid to mitigate the negative economic impact and job losses (Phan and Narayan, 2020). In the beginning of May 2023, the WHO declared that Covid was no longer a pandemic (WHO,2023).

The Covid-19 pandemic can be seen as a big test for the overreaction hypothesis. The Covid-19 pandemic was an unprecedented crisis which very little was known about in the beginning. Therefore, it led according to Phan and Narayan (2020), to a lot of fear. This fear induced the overreaction by governments and investors. Huo and Qiu (2020) concluded in their research of the Chinese stock market that during Covid-19 mostly retail investors overreacted which led to a price reversal. Researcher Vasileiou (2021) argues that Google searches for Covid-19 were correlated with stock market returns during the pandemic. This implies that rather than making rational decisions based on economic fundamentals, investors were making decisions based on emotions from the news about the pandemic. Smales (2021) found similar results and argues that negative sentiment on the stock market, increases the volatility. Based on these findings it appears that Covid-19 and investor sentiment have a relation. Researchers Ben-David, Graham and Harvey (2013) argue that in general the overreaction phenomenon is larger in times of high volatility.

In the early months of the pandemic equities went down and market volatility became sky high. Mid-March 2020 volatility had surpassed the December 2008 financial crisis level. At the end of March 2020 volatility went down but was still higher than pre-pandemic levels. Never had there been a pandemic that had such a big impact on the economy (Baker et al. 2020). Multiple researchers such as Albulescu (2021); Baek, Mohanty and Glambosky (2020) argue that Covid-19 new had a significant impact on the market volatility. According to Zaremba et al. (2020) the governmental non- pharmaceutical intervention also had an impact on the market volatility, independent of Covid-19.

2.4 Hypothesis

In the context of price reversals, multiple researchers such as De Bondt and Thaler (1985), Ma, Tang and Hassan (2005) have observed that extreme movements in stock prices, driven by overreaction, will be followed by subsequent price movements in the opposite direction. This observation leads to hypothesis 1 and 2:
H1: During COVID-19, a positive price reversal of more than 10% in stock prices leads to a negative cumulative average abnormal return (CAAR).

H2: During COVID-19, a negative price reversal, smaller than -10% in stock prices leads to a positive CAAR.

Extending the exploration to market characteristics, building on the insight of Researchers Zarowin (1990); Chopra, Lakonishok and Ritter (1992) and Banz (1981) who concluded that size matters and that firms who outperform are often smaller firms. The third hypothesis posits:
H3: During COVID-19, firm size is negatively associated with the CAAR, indicating that smaller firms are expected to exhibit a higher CAR.

Furthermore, multiple researchers such as Basu (1983); Rosenberg Reid and Lanstein (1985); Fama and French (1992) and Lakonishok, Shleifer and Vishny (1994) concluded that growth stocks exhibit on average lower returns than value stocks. This leads to hypothesis 4.
H4: During COVID-19, there is a negative influence on the CAAR if the stock is a growth stock compared to a value stock.

Moving on to financial metrics, based on the findings of researchers Pilloff (1996) and Berk and Demarzo (2017) the ROE is a profitability indicator and shows the capability of a company to capitalize on investment opportunities. A higher return on equity will result in a higher CAAR. This is examined in hypothesis 5:
H5: During COVID-19, the ROE has a positive impact on the CAAR.

Conrad and Kaul (1993) argue that a wider bid-ask spread leads to higher transaction cost and subsequently reduces abnormal returns, hypothesis 6 investigates the effect of the transaction cost on de CAAR in times of COVID-19.
H6: During COVID-19, the transaction cost has a negative effect on the CAAR.

Additionally, in the studies conducted by Amihud and Mendelson (1986); Bremer and Sweeney (1991); and Cox and Peterson (1994) an association between low liquidity and a higher return is observed. This leads to hypothesis 7.
H7: During COVID-19, higher values of liquidity are negatively associated with the CAAR.

In the study conducted by Piccoli and Chaudury (2018) the relationship between investor sentiment and the overreaction phenomenon is emphasized. They find that overreaction is more pronounced in times of low sentiment. To build on this insight, hypothesis 8 tests the effect of investor sentiment on the average CAR.
H8: During COVID-19, investor sentiment has a negative association with the CAAR.

Finally, according to the assertions of researcher Chan (1988) and Berk and DeMarzo (2020) when leverage is higher there is a higher idiosyncratic risk for the stockholders, potentially leading to diminished returns. This leads to hypothesis 9:
H9: During COVID-19, the leverage ratio is negatively associated with the CAAR.

3. Dataset and methodology

In the first part of this chapter, the collection of the data is described. The second part explains how to perform an event study, which determines the cumulative abnormal returns (CAR) and the last part discusses the regression which examines which factors influence the average cumulative abnormal returns (CAAR).

3.1 Dataset

For this research the data of the S&P500 is retrieved from Eikon-Datastream with period December 2019 till May 2023. Eikon-Datastream is a database that combines economic, financial and company data of shares, bonds, and derivatives. With this data individuals can monitor and analyze financial data. The S&P500 is chosen since it is the biggest exchange in America. The research period starts when the first cases of Covid-19 became public, in December 2019 and ends on May 5th, 2023, when the WHO declared Covid-19 to be over (WHO, 2023).

There are in total 567 unique companies for which first the variable price is retrieved from Datastream. The variable price is the average traded price for bonds. To identify the event dates a positive larger than 10% and a negative smaller than 10% trigger strategy is executed to mark all event dates for winner and loser stocks. There are 2 conditions which need to be met before an event date is used. If there are multiple companies on the same event date the most extreme value is used for that day. And if a company has two events within 120 trading days, the next largest value and company is used to avoid cross sectional correlation (Ma, Tang and Hassan, 2005). This results in 271 positive and 247 negative events. There are in total 257 unique companies for which the following variables have been retrieved via Datastream: the bid price, ask price, market value, volume, market to book value and debt-equity ratio, the Michigan Consumer Sentiment index, and the return on equity (ROE).

To control for volatility data from the CBOE volatility index are retrieved via the CBOE website. This variable shows the expected 9-day volatility of the S&P500. It is derived from the index options on the S&P500 which are about to expire, it therefore provides a forward look of the volatility.

3.2 The event study

To perform the event study the traditional framework from MacKinlay (1997) is used, which is depicted in Figure 3.1. With this framework an inference regarding the abnormal returns on the stocks can be made.

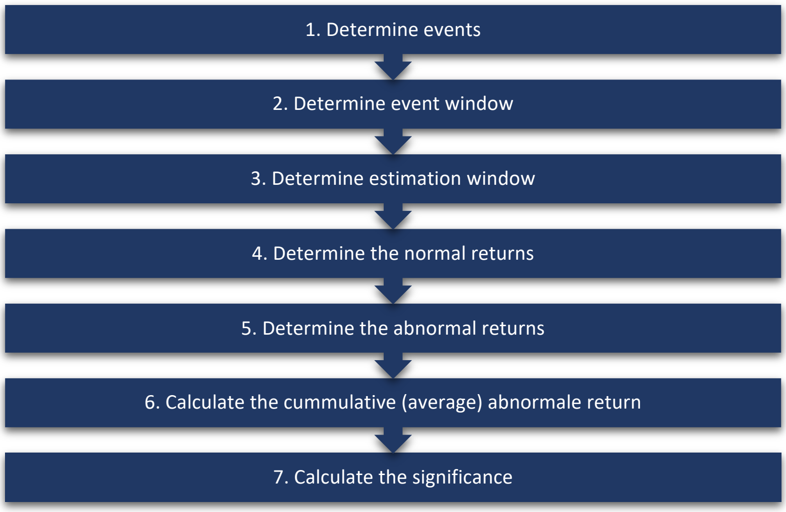

Figure 3.1 Steps of the event study.

The first step is to determine the events. The events are identified by the ±10% price trigger strategy of Bremer and Sweeney (1991). With this strategy a stock that has a price increase or decrease of more than 10% compared to the day before, is marked as an event day. According to the efficient market hypothesis from Fama, Fisher, French and Roll (1969) the market will adapt quickly to new information. However, due to the possibility of information leakages MacKinlay (1997) advises to take a window larger than 3 days. In this study a 3-day window and an 11-day event window are used.

The estimation window is 120 days, since Brown & Warner (1985) suggest that to determine the normal returns on stocks a window between 115-120 days should suffice, see figure 3.2 for an overview of the event study timeline. The normal returns are the expected returns of the stock with the assumption that the event wouldn't have taken place. Therefore, if a company is flagged twice within 120 days as an event, the event date is removed from the sample to avoid a biased estimation window. In this paper the market model is used to determine the normal returns, see formula 1, and the benchmark is the S&P 500 index.

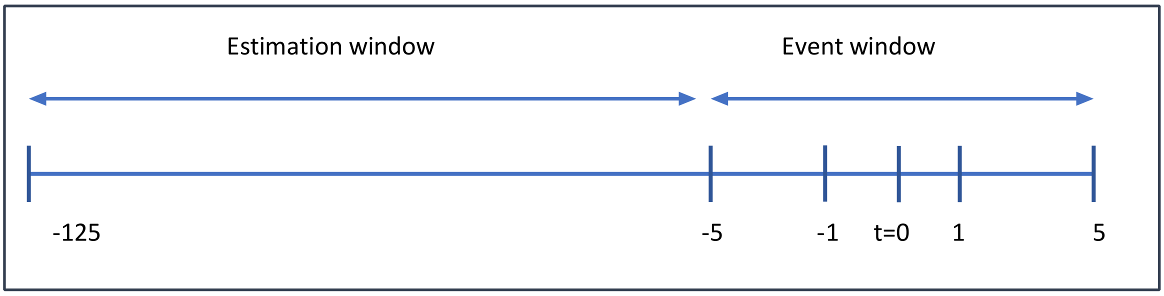

Figure 3.2 Timeline of the event study.

Formula of the normal returns:

$$R_{\mathrm{it}} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it} \tag{1}$$

R_{it} equals the normal return of the stock i on time t, α_i is the constant of effect i, β_i equals the sensitivity of the stock compared to the market portfolio. Variable R_{mt} equals the return on the S&P500 market index on time t and the last variable ε_{it} is the error term of stock i on time t where t stands for time in days.

The daily returns are calculated with formula 2:

$$Daily\ return_t = \frac{closing\ price_t - closing\ price_{t-1}}{closing\ price_{t-1}} \tag{2}$$

Where t stands for time in days.

The abnormal returns arise when there is a difference between the realized returns and the normal returns. Normally the returns are calculated by formula 3, however when using the market model the formula is adjusted as can be seen in formula 4.

$$Abnormal\ returns = realized\ returns - normal\ return \tag{3}$$

$$Abnormal\ returns\ marketmodel = stock\ return - \alpha - index\ return * \beta \tag{4}$$

Here the stock return equals the realized return on stock i, α is the constant of stock i, and the $index\ return$ is the realized returns of the index. The variable β equals the sensitivity of the stock compared to the market portfolio.

With this data the cumulative abnormal returns (CAR) and the average cumulative abnormal returns (CAAR) are calculated.

The CAR, formula 5, is a summation of all the abnormal returns over the entire time frame.

The CAAR, formula 6, is the average of the CAR.

$$CAR = \sum_{i=1}^{N}(AR) \tag{5}$$

$$CAAR = \frac{1}{N}\sum_{i=1}^{N}(AR) \tag{6}$$

To test for significance a t-test is used with a null hypothesis of the CAR and CAAR are equal to zero, see formula 7. The critical value used is ±1.96 with a 95% confidence interval.

$$tCAR = \frac{CAR_{t1,t2}}{SCAR/\sqrt{n}} \tag{7}$$

where:

$CAR_{t1,t2}$= CAR of the event window

$SCAR$ = standard deviation of the CAR

n = amount of stocks

3.3 Regression model

To test multiple hypotheses which are mentioned in chapter 2 a multivariate regression is used. The dependent variable is the cumulative abnormal return, and the independent variables are the size, whether a company is a growth stock or not, transaction cost, the return on equity, the liquidity of the firm and the market sentiment.

To test hypothesis 3 *"during COVID-19, firm size is negatively associated with the CAAR, indicating that smaller firms are expected to exhibit a higher CAR"* the following regression is tested:

$$CAR_i = \alpha + \beta_1 * (Size) + \varepsilon t \tag{8}$$

Variable $\beta_1 * (Size)$ is a continuous variable which depicts the size of a firm based on the company's market value. The expectation is that β_1 is negative since the abnormal returns are lower when firm size is bigger (Zarowin, 1990).

To test hypothesis 4 *"during COVID-19, there is a negative influence on the CAAR if the stock is a growth stock compared to a value stock",* the following regression is tested:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \varepsilon t \quad (9)$$

Variable $\beta_2 * (Growth\ stock)$ is a dummy variable that takes on a value of 1 if the company belongs to the group with a market to book in the lowest 30%, otherwise it takes on the value 0. With this the comparison between the impact of a value and growth stock can be made. The expectation is that β_2 will be negative since multiple researchers such as Basu (1983); Rosenberg Reid and Lanstein (1985); Fama and French (1992) concluded that growth stocks have on average a lower return than value stocks.

To test hypothesis 5 *"during COVID-19, the ROE has a positive impact on the CAAR"* the following regression is used:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \beta_3 * (ROE) + \varepsilon t \quad (10)$$

Variable $\beta_3 * (ROE)$ is a continuous variable which depicts the net income divided by the average value of equity. It is expected that β_3 will have a positive value since researchers Pilloff (1996) and Berk and Demarzo (2017) state that the ROE is a profitability indicator and shows the capability of a company to capitalize on investment opportunities. A higher return on equity should result in a higher CAR.

To test hypothesis 6 "*during COVID-19, the transaction cost has a negative effect on the CAAR'* the following regression is tested:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \beta_4 * (Transaction\ cost) + \varepsilon t \quad (11)$$

Variable $\beta_4 * (Transaction\ cost)$ is a continuous variable and depicts the transaction cost which is measured by the difference between the ask and bid price. The expectation is that β_4 will be negative based on the findings of researchers Conrad and Kaul (1993).

To test hypothesis 7 *"during COVID-19, higher values of liquidity are negatively associated with the CAAR"* the following regression is tested:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \beta_4 * (Transaction\ cost) + \beta_5 * (Liquidity) + \varepsilon t \quad (12)$$

Variable $\beta_5 * (Liquidity)$ is a continuous variable which depicts the liquidity of a stock. This is a measurement of how easy an asset can be bought or sold. Multiple researchers, Amihud and Mendelson (1986), Cox and Peterson (1994) and Bremer and Sweeney (1991) found that stock with low liquidity tend to produce higher returns. Therefore, the expectation is that β_5 will be negative.

To test hypothesis 8, *"during COVID-19, investor sentiment has a negative association with the CAAR"* the following regression is tested:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \beta_4 * (Transaction\ cost) + \beta_5 * (Liquidity) + \beta_6 * (Market\ sentiment) + \varepsilon\mathrm{t} \qquad (13)$$

Variable $\beta_6 * (Market\ sentiment)$ is based on the Michigan Consumer Sentiment Index. A higher score on the index depicts more confidence in the market from individuals. Based on the research of Piccoli and Chaudury (2018) who state that the overreaction is more pronounced in times of low investor sentiment, it is expected that β_6 will be negative.

To test hypothesis 9, *"during COVID-19, the leverage ratio is negatively associated with the CAAR"* we test the following regression:

$$CAR_i = \alpha + \beta_1 * (Size) + \beta_2 * (Growth\ stock) + \beta_4 * (Transaction\ cost) + \beta_5 * (Liquidity) + \beta_6 * (Market\ sentiment) + \beta_7 * (Leverage) + \varepsilon\mathrm{t} \qquad (14)$$

Variable $\beta_7 * (Leverage)$ is a continuous variable which contains the debt-to-equity ratio. A higher debt to equity ratio equals a higher leverage. When the leverage is higher there is a higher idiosyncratic risk for stockholders. This could imply that the return on the stock will be lower (Berk and DeMarzo, 2017) and therefore the expectation is that β_7 will be negative.

3.4 Descriptive statistics

In table 3.1 the event studies with the positive price reversals of more than 10% are described, for the 3-day (-1,1), and 11-day (-5,5) window. For both windows the CAR, intercept, and slope are depicted. The same variables we see in table 3.2 for negative reversals of less than -10%. For panel A, positive price reversals, there is a total of 261 observations and on average these stocks outperformed the market with a CAAR of 0.091 for the 3-day window and 0.083 for the 11-day window. The average intercept for both windows is zero, which implies that the positive abnormal returns are attributed to general market movements. Slope 1 and slope 2 are larger than 1, 1.109 and 1.100 respectively, this suggest that the stocks with the price reversal are more volatile compared to the market. For the panel B, negative price reversals, there is a total of 246 observations with a mean of -0.156 and -0.146 for the CAR (-1,1) and CAR (-5,5) respectively. The negative CARs imply that the stocks underperformed in these event windows. Similar to the positive price reversals, the intercepts for both windows are zero and the slopes are larger than 1, 1.234 and 1.229 for the 3-day and 11-day, respectively. According to these observations, the market model appears to fully explain the CAR of the negative price reversals. Additionally, the stocks with the price reversals exhibit a higher volatility than the market.

Table 3.1 Descriptive statistics of the event study based on the positive price reversals.

This table presents the descriptive statistics of the event study results based on the positive price reversals, using the market model. The CAR(-1,1) depicts the cumulative abnormal returns for the 3-day event window and the CAR(-5,5) depicts the cumulative abnormal return for the 11-day window. For both event windows the number of observations (obs.), the mean, the standard deviation (std. dev.) the minimum (min.), and maximum (max.) are depicted for the variables CAR, intercept, and slope. The intercept indicates the alpha in the market model which is the average abnormal performance of the stock which is not explained by the market model. And the slope depicts the beta in the market model and is the responsiveness of the stocks return to the market returns.

Panel A: CAR of positive price reversals					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CAR (-1,1)	261	0.091	0.115	-0.549	0.614
Intercept 1	261	0.000	0.002	-0.010	0.005
Slope 1	261	1.109	0.458	0.013	2.637
CAR (-5,5)	261	0.083	0.145	-1.301	0.469
Intercept 2	261	0.000	0.002	-0.008	0.006
Slope 2	261	1.100	0.479	-1.737	2.454

Table 3.2 Descriptive statistics of the event study based on the negative price reversals.

This table presents the descriptive statistic for the event study results based on the negative price reversals. The CAR(-1,1) depicts the cumulative abnormal returns for the 3-day event window and the CAR(-5,5) depicts the cumulative abnormal return for the 11-day window. For both event windows the number of observations (obs.), the mean, the standard deviation (std. dev.) the minimum (min.), and maximum (max.) are depicted for the variables CAR, intercept, and slope. The intercept indicates the alpha in the market model which is the average abnormal performance of the stock which is not explained by the market model. And the slope depicts the beta in the market model and is the responsiveness of the stocks return to the market returns.

Panel B: CAR of negative price reversals					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CAR (-1,1)	246	-0.156	0.101	-0.635	0.420
Intercept 1	246	0.000	0.003	-0.008	0.011
Slope 1	246	1.234	0.434	-0.033	2.811
CAR (-5,5)	246	-0.146	0.154	-1.008	0.440
Intercept 2	246	0.000	0.003	-0.01	0.012
Slope 2	246	1.229	0.438	-0.05	2.799

To check for robustness the winners and losers have been divided into 2 groups. The first winner group contains price reversals between 10-20%, while the second winner group contains price reversals larger than 20%. For the losers, the first group includes price reversals between -10% and -20% and the second group consists of reversals smaller than -20%. The results are displayed in table 3.3.

For the winners the CAAR remains positive. In the 3-day window, the CAAR is 0.133 for the first winner group and is 0.278 in the second winner group. In the 11-day window the CAAR is 0.127 for the first group and 0.207 for the second. Compared to panel A the CAAR of the first group is slightly higher. However, for the second group the CAAR has doubled compared to Panel A and to group 1. This can be explained by the fact that the second group contains extreme price reversals of more than 20%, resulting in fewer observations (58) compared to Panel A and group 1. Panel A includes price reversals of larger than 10% and group 1 includes price reversals between 10% and 20% which have respectively 246 and 260 observations. The extreme reversals are less likely to occur. The rarity of the extreme positive price reversals might contribute to the higher observed CAAR.

For the losers the CAAR remains negative. The first loser group results in a CAAR of -0.120 for both event windows and the second loser group results in -0.284 for the 3-day window and -0.326 for the 11-day window. Compared to panel B the results for the first group are slightly lower. However, for the second group for the 3-day window the result has decreased with

82% and for the 11-day window the CAAR decreased with 123%. This can be explained by the same logic that holds for the positive extreme reversals. The extreme negative reversals have less observations (50) compared to 241 for the first group and 246 in the total panel. The rarity of extreme negative price reversals might add to the lower observed CAAR.

Table 3.3 Descriptive statistics of the event study based on the grouped price reversals.

This table present the descriptive statistics of the results for the grouped event studies. The winners have been categorized into 2 groups: group 1, with price reversals between 10% and 20% and group 2, with reversals larger than 20%. The losers are categorized into 2 groups: group 1, with price reversals between -10 and -20%, and group 2, with reversals smaller than -20%. For these groups the number of observations, the mean, the standard deviation (std, dev.), the minimum (min.), and the maximum (max.) are shown for the 3-day and 11-day event windows, CAR(-1,1) and CAR (-5,5), respectively.

	Winners		**Losers**	
Variable	**10% -20%**	**>20%**	**-10% and -20%**	**<-20%**
CAR (-1,1)				
Observations	260	58	241	50
Mean	0.133	0.278	-0.120	-0.284
Std. dev.	0.073	0.202	0.069	0.119
Min.	-0.131	-0.549	-0.459	-0.635
Max.	0.494	1.033	0.105	-0.093
CAR (-5,5)				
Observations	260	58	241	50
Mean	0.127	0.207	-0.120	-0.326
Std. dev.	0.125	0.256	-0.125	0.303
Min.	-0.490	-1.301	-0.602	-1.588
Max.	0.581	0.485	0.360	0.119

For the regression on the CAAR multiple variables are used. Table 3.4 provides the descriptive statistics for following variables: the size of the company, the ROE, transaction cost, liquidity, market sentiment, leverage and the VIX.

The variable size of the company is depicted by the natural logarithm of the variable market value. This represents the amount of ordinary shares times the share price for each company in millions of dollars. The natural logarithm is taken to reduce skewness. The variable ROE illustrates the return of equity of the firm and is calculated by dividing the net income minus preferred dividends over the average common equity.

The variable transaction cost is calculated by deducting the bid price from the ask price. The bid price is the average price individuals are willing to pay for the asset. While the ask price is the average price at which a seller will accept the bid at times the market closes.

The variable liquidity is represented by the volume. The variable volume depicts the daily turnover of the security. The natural logarithm of this variable is taken to reduce skewness. The market sentiment is based on the Michigan Sentiment Consumer Index. The MSCI is a monthly survey that reflects the confidence of U.S. consumers. A higher MSCI value indicates greater confidence in the market. The debt equity ratio shows the ratio of long term and short-term debt over common equity. This will be used as a proxy for leverage. The D/E variable undergoes winsorization at 10% and 99% to mitigate skewness and eliminate negative ROE. The variable VIX is the volatility index, it reflects the market volatility over the next 9 days, a lower value indicates a more stable environment.

The variable market to book ratio is the market value of outstanding ordinary common equity divided by the balance sheet value of the common equity. This is used to classify whether a stock is a value, growth, or neutral stock. The negative market to book ratios have been removed, since according to Fama and French (1995) this depicts companies who are in financial distress rather than being a growth stock. Next, the natural logarithm is taken to have a more natural distribution. The variable is then split up in to 3 dummy variables like the methodology used by Karan and Gonec (2003). The lowest 30% are growth stocks, the middle 40% are neutral stocks and the highest 30% are value stocks. The description of the dummy variables is shown in table 3.5.

All variables are utilized on a daily frequency. The variables ROE and market to book value are retrieved on a yearly basis and the market sentiment monthly. To incorporate it in the regression the yearly or monthly value is assigned to each day of the month allowing for a daily representation of the variable. This methodology is chosen to enhance the granularity of the analysis.

Table 3.4 Descriptive statistics of the dependent and independent variables.

Descriptive statistics of dependent and independent variables. The dependent variable is the CAR(-1,1) and CAR(-5,5) which contains the sum of the CAR of the positive panel and the negative panel. The variable size is depicted by the natural logarithm of the market value of the stock. The ROE depicts the return on equity, Transaction cost is the ask price minus the bid price and the liquidity is represented by the market volume. The market sentiment is based on the Michigan Consumer Sentiment Index and leverage depicts the debt-to-equity ratio. The VIX is the volatility index.

Variable	Observations	Mean	Std. Dev.	Min.	Max.	Skew.
CAR(-1,1)	507	-0.029	0.164	-0.635	0.614	0.111
CAR (-5,5)	507	-0.028	0.188	-1.301	0.469	-1.266
ln Size	283,697	10.037	1.189	1.426	14.905	0.474
ROE	241,845	35.770	303.760	-1707.02	6,575.940	18.321
Transaction cost	265,799	0.060	0.150	-0.140	6.190	14.296
Liquidity	265,949	6,458.113	16,602.900	0.000	914,081.30	9.773
Market sentiment	284,928	72.380	12.420	50.000	101	0.452
Leverage	259,245	166.105	313.417	1.860	2180.230	4.331
VIX	274,434	23.820	12.530	10.050	99.940	3.285

Table 3.5 Descriptive statistics for the dummy variables.

This table displays the descriptive statistics for the dummy variables growth stock, neutral stock, value stock based on the market to book value. The variable takes on a value 1 if the stock belongs to the respective category and 0 otherwise.

Variable	Frequency	Percentage %	Cumulative %
Growth stock	214,458	75.27	75.27
Neutral stock	49,933	17.52	92.97
Value stock	20,537	7.21	100

To assess multicollinearity, a correlation test is conducted between all explanatory variables, and the results are presented in table A, Appendix A. In the correlation table, where a correlation of 1 indicates perfectly correlated and -1 perfectly inverse correlated, all variables exhibit correlations below 0.35 or above -0.10. Therefore, it can be inferred that there is no significant multicollinearity.

Next, a Whitetest is conducted to examine if there is homoskedasticity. This test assesses whether the variance of the error term is constant. The result of the Whitetest is 103.231 with a p-value of 0.000 since this is smaller than the critical value of p (0.05) it is unlikely that there is homoscedasticity. To address this the robust function is used to control for potential issues arising from heteroskedasticity.

4. Results

In this section the results will be presented, addressing the hypothesis formulated to explore various variables which possibly influence the stock returns during COVID-19.

To test the first hypothesis *'during COVID-19 a positive price reversal of more than 10% in stock prices leads to a negative cumulative average abnormal (CAAR) return'* an event study has been performed on the positive 1-day price reversals larger than 10%. To test for robustness the price reversals have been further categorized into 2 groups: group 1 contains the reversals between 10-20% and group 2 the reversals larger than 20% group. The results, as presented in table 4.1, reveal a positive average cumulative return of the entire panel with a value of 0.091 based on the 3-day (-1,1) window, and 0.083 for the 11-day (-5,5) window. Both returns are statistically significant at the 0.01 level. Similarly, in the panel of 10-20% the CAAR for the 3-day window is 0.133 and for the 11-day window it is 0.127, both statistically significant at the 0.01 level. For the larger than 20% panel, the average CAARs for the 3-day and 11-day window are 0.278, 0.207 respectively, both are statistically significant at the 0.01 level. Thus, the first hypothesis is rejected, indicating that there is no support to assume that during COVID-19 a one day increase in stock price of more than 10% leads to a negative cumulative return.

Table 4.1 Results of the event study for the (grouped) positive price reversals.

This table shows the CAAR results of the positive panel of event study for the 3-day window CAAR (-1,1) and the 11-day window CAAR (-5,5). The positive panel is categorized as , the total panel of >10%, a group between 10-20% and a group of >20%.

	Positive panel A		
Variable	**Total >10%**	**10% -20%**	**>20%**
CAAR (-1,1)	0.091*** (0.115)	0.133*** (0.073)	0.278*** (0.202)
CAAR (-5,5)	0.083*** (0.145)	0.127*** (0.125)	0.207*** (0.256)

*Standard deviations are between brackets;*p<0.10, **p<0.05,***p<0.01.*

For the second hypothesis *'during COVID-19 a negative price reversal of less than -10% in stock prices leads to a positive CAAR',* the negative 1-day price reversals are utilized in an event study. The total negative panel is further divided into 2 groups: the first group with price reversals between -10% and -20% and the second group with reversals smaller than -20%. The results, outlined in table 4.2, show a negative CAAR for the total negative panel in the 3- and 11-day event windows, with the values -0.156 and -0.146 respectively. Both are statistically significant at the 0.01 level. For group 1 the CAAR equals -0.120 for both the 3-day and 11-day window and are statistically significant at the 0.01 level. For group 2 the CAAR equals -0.248 for the 3-day window and -0.326 for the 11-day window. Both CAARs are statistically significant at the 0.01 level. Therefore, hypothesis 2 is rejected, providing no evidence to support the notion that during COVID-19 a one-day price reversal of less than -10% in stock prices leads to a positive CAAR.

Table 4.2 Results of the event study for the (grouped) negative price reversals.

This table shows the CAAR results of the negative panel of event study for the 3-day window CAAR (-1,1) and the 11-day window CAAR (-5,5). The negative panel is categorized as the total panel of < -10%, a group between -10 and -20% and a group of < -20%.

Negative panel B			
Variable	**Total <-10%**	**-10 and -20%**	**< -20%**
CAAR (-1,1)	-0.156*** (0.101)	-0.120*** (0.069)	-0.284*** (0.119)
CAAR (-5,5)	-0.146*** (0.154)	-0.125*** (-0.602)	0.303*** (-1.588)

*Standard deviations are between brackets;*p<0.10, **p<0.05, ***p<0.01.*

The findings of H1 and H2 align with those of researchers Cox and Peterson (1994) and Arbel and Jaggi (1982), who examined the US market and did not find significant results supporting the overreaction hypothesis. In addition, these findings suggest that in the short term, investors may find the momentum strategy more favorable than the contrarian strategy, aligning with the results of Jegadeesh and Titman (1993).

For the hypotheses 3-9 multiple regressions are conducted on the 3-day CAR and 11-day CAR, as specified in chapter 3.3. The dependent variable in these regressions is the total of the positive and negative CARs. Rather than treating them separately, they are combined in a unified variable. This approach is chosen to capture the overall impact on the price reversal, regardless of the direction of the reversal. The regression results are presented in table 4.3 where the column labels H3-H9 represent the hypothesis 3-9. The 3-day CAAR will be referred to as model 1 and the 11-day CAAR as model 2.

For hypotheses 3 *"During COVID-19, firm size is negatively associated with the CAAR, indicating that smaller firms are expected to exhibit a higher CAR"*, is tested what effect the variable (firm) size has on the CAAR. The coefficient of the variable size is unexpectedly positive. The coefficient has a value of 0.007, suggesting that a one-unit increase in the natural logarithm of the variable size is associated with an increase in the dependent variable CAAR with 0.7%. However, this result lacks statistical significance. Across 14 regressions, variable size consistently fails to show a negative coefficient, and the results are not statistically significant, except for hypothesis 7 and 8 in model 1 and hypothesis 8 and 9 in model 2. These coefficients are respectively, 0.012, 0.013, 0.014 and 0.012 and are statistically significant at the 10% level. These results are not in line with Zarowin (1990) who concluded that smaller firms experience higher CARs. In summary, there is no compelling evidence that firm size is negatively associated with the CAAR and that smaller firms exhibited a higher CAR than larger firms during COVID-19. Consequently, hypothesis 3 is rejected based on the subset of significant outcomes.

To test hypotheses 4, "*during COVID-19, there is a negative influence on the CAAR if the stock is a growth stock compared to a value stock*, a dummy variable representing growth stock is included in addition to the variable size from H3. The variable growth stock consistently has a negative coefficient across all 12 regressions, as expected ex-ante. In the first model, the results of H4 display a coefficient of -0.036 which is statistically significant at the 5% level. This indicates, that compared to a value stock, the CAAR of the growth stocks will be 0.036 units lower. The growth stock coefficients in model 1 of H5, H6, H7 are -0.028, -0.030, -0.028 and are statistically significant at 10%. In the second model, dummy variable growth stock is statistically significant at the 5% level for H4 with a coefficient of -0.044. Indicating that compared to a value stock, the growth stock's CAAR will be -0.044 units lower. Additionally, the variable is statistically significant at the 10% level for H6, H7 and H8. With a coefficient of -0.037, -0.036, -0.033, respectively. Based on these results, the inference is that there is a negative influence on the CAAR if the stock is a growth stock compared to a value stock, and therefore hypothesis 4 is not rejected. This conclusion is in line with that of scholars Basu (1983); Rosenberg Reid and Lanstein (1985); Fama and French (1992).

To examine hypothesis 5, asserting that *"during COVID-19, the ROE has a positive impact on the CAAR"* the variable return on equity is added into the regression model used for hypothesis 4. For model 1 and 2 the ROE surprisingly yielded a coefficient of 0.000 and lacked statistical significance. Furthermore, the inclusion of the ROE led to a reduction in the model's explanatory power, as reflected with a decrease in the R^2-value by 0.004 in model 1 and 0.005 in model 2. This decline suggests that the addition of the ROE did not contribute meaningfully to this model. Given these results and the absence of mention in the existing literature, the variable is excluded from further regressions. Consequently, hypothesis 5 is not supported by empirical evidence and fails to be rejected.

To test hypothesis 6 *"during COVID-19, the transaction cost has a negative effect on the CAAR"* the variable transaction cost is added to the regression from H4. In regression H6 the coefficients are 0.044 in model 1 and 0.03 in model 2, both are not statistically significant. Subsequently, when testing hypotheses 7-9 the results of variable transaction are inconsistent. In both models the value sign changes twice. In model 1, the coefficient shifts from 0.044 to -0.037 when incorporating the variable liquidity and back to a positive value of 0.015 when adding variables leverage and VIX. In model 2 the coefficient shifts from 0.03 to -0.059 and returns to 0.004. This outcome is surprising, especially considering the low correlation between the transaction cost variable and liquidity (-0.084) and leverage (0.014). Across all 8 regressions, the coefficient remains statistically insignificant. Due to the lack of statistical evidence, hypothesis 6 is not supported and fails to be rejected.

To test hypothesis 7 *"during COVID-19, higher values of liquidity are negatively associated with the CAAR"*, the variable liquidity is added to the regression from H6. In both models the coefficient of the variable liquidity is negative measuring -0.017 in model 1 and -0.018 in model 2. These results are in line with the ex-ante expectation. For all 6 regressions the coefficients demonstrate statistical significance at the 1% level, except for model 2, H9 there the 5% level holds. This suggest that if the natural logarithm of liquidity increases with one unit, the CAAR will decrease with 1.7% in model 1 and 1.8% in model 2. Consequently, these outcomes suggest that liquidity negatively influences the CAAR, therefore hypothesis 7 is not rejected. This result is in line with that of researchers Cox and Peterson (1994) and Bremer and Sweeney (1991) who concluded that low liquidity leads to higher returns.

To test hypothesis 8 *"During COVID-19, investor sentiment has a negative association with the CAAR"* the variable investor sentiment is added to the regression from H7. In both models the coefficients are unexpectedly positive with a value of 0.001 in model 1 for H8 and H9, statistically significant at the 5% and 10% level, respectively. In model 2 the value for H8 and H9 are both 0.002, and significant at the 1% level. Including the variable investor sentiment increased the explanatory power in model 1 from 0.023 to 0.041 and in model 2 from 0.030 to 0.047. Consequently, the outcomes suggest that higher investor sentiment will lead to a higher

CAAR, therefore hypothesis 8 is rejected. This conclusion is in line with Stambaugh et al. (2012) who find greater anomalies when investor sentiment is high.

To examine hypothesis 9 *"During COVID-19, the leverage ratio is negatively associated with the CAAR"* the variable leverage is added to the regression of H8. The coefficient of the leverage variable equals 0.000 for both models and is not statistically significant. The inclusion of this variable reduces the explanatory power of model 1 from 0.041 to 0.030 and in model 2 from 0.047 to 0.035. This decline suggests that the addition of the leverage did not contribute meaningfully to this model. Consequently, hypothesis 9 is not supported by empirical evidence and fails to be rejected.

Table 4.3 Results of the linear regression models for the combined CAR.

This table presents the linear regression results for the relation between the dependent variables combined CAR(-1,1) which is the cumulative abnormal return for the 3-day event window of price reversals larger than 10%, sign ignored. And the combined CAR(-5,5) which is the cumulative abnormal return for the 11-day event window of price reversals larger than 10%, sign ignored. And the independent variables: size of the company, whether the stock is a growth stock, ROE, transaction cost, liquidity, investor sentiment and leverage. The variable VIX, represents the volatility index and is a control variable. The headers in row 2, H3-H9, depict hypothesis 3-9.

	Model 1: Combined CAR(-1,1)							Model 2: Combined CAR (-5,5)						
Variable	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**
Size	0.007 (0.008)	0.005 (0.007)	0.003 (0.008)	0.009 (0.007)	0.012* (0.007)	0.013* (0.007)	0.011 (0.007)	0.007 (0.008)	0.004 (0.007)	0.003 (0.007)	0.008 (0.007)	0.012 (0.007)	0.014* (0.007)	0.012* (0.007)
Growth stock		-0.036** (0.016)	-0.028* (0.019)	-0.03* (0.016)	-0.028* (0.016)	-0.026 (0.016)	-0.032 (0.025)		-0.044** (0.019)	-0.033 (0.022)	-0.037* (0.019)	-0.036* (0.019)	-0.033* (0.019)	-0.026 (0.033)
ROE			0.000 (0.000)							0.000 (0.000)				
Transaction cost				0.044 (0.072)	-0.037 (0.072)	-0.024 (0.073)	0.015 (0.074)				0.03 (0.075)	-0.059 (0.075)	-0.037 (0.075)	0.004 (0.078)
Liquidity					-0.017*** (0.005)	-0.016*** (0.005)	-0.015*** (0.005)					-0.018*** (0.007)	-0.018*** (0.006)	-0.015** (0.006)
Investor sentiment						0.001** (0.001)	0.001* (0.001)						0.002*** (0.001)	0.002*** (0.001)
Leverage							0.000 (0.000)							0.000 (0.000)
VIX							0.000 (0.001)							0.000 (0.001)
Constant	-0.096 (0.079)	-0.051 0.082	-0.036 (0.080)	-0.093 (0.075)	0.026 (0.076)	-0.080 (0.094)	-0.054 (0.089)	-0.092 (0.078)	-0.037 (0.083)	-0.032 (0.078)	-0.081 (0.076)	0.049 (0.081)	-0.127 (0.103)	-0.114 (0.100)
Obs.	507	507	424	498	498	498	462	507	507	424	498	498	498	462
R^2	0.003	0.012	0.008	0.014	0.023	0.041	0.03	0.020	0.011	0.016	0.013	0.030	0.047	0.035

Standard errors are between brackets; *p<0.10, **p<0.05, ***p<0.01

5. Conclusion

To conclude, this thesis aims to explore the applicability of the overreaction hypothesis on the S&P500, in times of crisis, specifically the COVID-19 pandemic. The central research question was whether regular investors could benefit from the overreaction hypothesis on the S&P500 during COVID-19. The findings reveal a nuanced picture.

The results of the examination of hypotheses 1 and 2 align with prior work by researchers Cox and Peterson (1994) and Arbel and Jaggi (1982), indicating a lack of statistically significant support for the overreaction hypothesis in the US stock market. However, these results suggest that investors could utilize the momentum strategy on the short term, to benefit from a price reversal, echoing the findings of Jegadeesh and Titman (1993).

Proceeding to hypotheses 3-9, various regressions were performed on the 3-day and 11-day cumulative abnormal returns. Notably, hypothesis 3 suggesting a negative association between firm size and CAAR was rejected, contrary to the anticipated outcomes based on the findings of Zarowin (1990). Additionally, hypothesis 5, proposing a positive association between the ROE and CAAR, lacked empirical support and was consequently eliminated from further regressions analyses.

Hypotheses 4,6,7,8 and 9 offered a range of insight. In hypothesis 4 the growths stocks, exhibited a negative influence on the CAAR compared to value stocks. Hypothesis 6, Transaction cost demonstrated the anticipated positive impact on the CAAR. Furthermore, in hypothesis 7, which examined liquidity, the expected negative influence on the CAAR was observed. However, hypothesis 8, exploring investor sentiment, revealed a surprising positive association contrary to the negative ex-ante expectation. Lastly, hypothesis 9 which examined the association between the leverage ratio and the CAAR, was not supported by empirical evidence.

These findings highlight the complex and varied nature of market dynamics during crises. Some hypotheses yielded surprising outcomes, indicating that investor behavior is not in line with the conventional expectations in times of crisis. These insights enhance our understanding of the market.

To summarize, based on the results of this paper regular investor are unlikely to gain from the overreaction hypothesis on the S&P500 during COVID-19 in the short term. Instead, employing a momentum strategy may offer more advantages. Firm characteristics such as whether a stock is a value or growth stock, liquidity and investor sentiment could be valuable factors for investors when composing a trading strategy.

This paper has certain limitations. First, the calculation of the abnormal returns relies on the market model. Besides, while behavioral biases that appear to be contributors to irrational behavior are recognized in the literature, their incorporation into the methodological framework is not explicitly addressed in this study.

An avenue for further exploration could involve narrowing the focus to examine only growth stocks from innovative companies in Europe or Asia, since a considerable portion of the existing literature is based on the US market.

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Appendix A Correlation table

Table A Correlation table between the independent variables

This table show the results of the correlation test between independent variables, size, market to book value, ROE, transaction cost, liquidity, market sentiment, leverage and the VIX. A result of 1 indicates perfect positive correlation and a result of -1 indicates perfect negative correlation.

	Size	**MB value**	**ROE**	**Transaction cost**	**Liquidity**	**Market sentiment**	**Leverage**	**VIX**
Size	1							
MB value	0.327***	1						
ROE	0.032***	0.225***	1					
Transaction cost	0.084***	0.273***	0.084***	1				
Liquidity	0.320***	-0.012***	-0.023	-0.084	1			
Market sentiment	-0.014***	0.026***	0.020***	0.001	0.000	1		
Leverage	-0.034***	0.264***	-0.034***	0.014***	0.013***	-0.008***	1	
VIX	-0.074***	-0.057***	-0.009***	0.001	0.057***	-0.060***	0.018***	1

**p<0.10, **p<0.05, ***p<0.01.*