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SHORT-TERM OVERREACTION IN THE US STOCK MARKET DURING THE COVID-19 PANDEMIC

THE DISTINCTION BETWEEN VALUE AND GROWTH STOCKS

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PREFACE AND ACKNOWLEDGEMENTS

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ABSTRACT

This study examines the short-term overreaction for NYSE stocks during the COVID-19 pandemic. An event study has been used to test whether regular investors could have profited from this overreaction by conducting a contrarian investment strategy, after controlling for transaction costs, firm size, liquidity, investor sentiment and risk. For both large one-day price declines and increases, evidence for a price reversal effect is found in the subsequent days, supporting the overreaction hypothesis. However, this reversal is also partly attributable to the bid-ask bounce and risk-change effect. Further, this paper finds that investors undervalue value stocks and overvalue growth stocks.

Keywords: Overreaction hypothesis, Price reversal effect, Contrarian investment strategy, Value versus growth stocks, US stock market, COVID-19 pandemic

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CHAPTER 1 Introduction

Existing literature has thoroughly documented a phenomenon in the stock markets, which is known as the price reversal effect. The effect refers to the occurrence of large one-day stock price movements with subsequent movements in the reversed direction. This pattern might be explained by the 'overreaction hypothesis', which states that investors tend to overreact to unexpected news, causing large stock price movements that are corrected in the following days by movements in the opposite direction. Individuals often rely excessively on the similarity of past events when determining the probability of future events (Kahneman & Tversky, 1972). De Bondt and Thaler (1985) applied this concept to the stock market and concluded that investors overreacted to unexpected news, as they overvalued recent information and undervalued past information. After reevaluating the security's value, they adjust their overreaction, causing the stock price reversal. Prior studies found that the magnitude of the short-term price reversal is greater for stocks that experience a large one-day price decrease ('loser' stocks) than for stocks that experience a large one-day price increase ('winner' stocks) (Bowman & Iverson, 1998). Chan (1988) also concluded that losers outperform winners because of short-term overreaction. Besides, he argued that investors could leverage these findings about overreaction and price reversals by employing a 'contrarian investment strategy', which involves buying losers and shorting winners.

Many research has been conducted on the profitability of this contrarian investment strategy. However, limited research has examined whether this investment strategy is still profitable after having accounted for transaction costs, firm size, liquidity, investor sentiment and risk, as the literature proposed these as alternative explanations for the price reversal effect. Conrad and Kaul (1993) suggested that measurement inaccuracies arising from the bid-ask bounce could explain the abnormal returns. Zarowin (1990), on the other hand, questioned the overreaction hypothesis and attributed the outperformance of loser portfolios to the size effect. Moreover, factors such as liquidity (Cox & Peterson, 1994), investor sentiment (Piccoli & Chaudhury, 2018) and changes in risk (Chan, 1988) have been argued as possible explanations for the profitability of contrarian investment strategies. Hence, this study aims to contribute to the existing literature by addressing the following research question:

Could regular investors in the U.S. stock market have profited from the overreaction hypothesis during the COVID-19 pandemic, if transaction costs, firm size, liquidity, investor sentiment and risk have been accounted for?

To answer the abovementioned research question, this research uses data from the stock returns of New York Stock Exchange (NYSE) companies that were listed on the NYSE during the entire period from 11/03/2020 till 30/06/2022. In order to examine the short-term price reversal effect, this paper analyses the (cumulative) abnormal returns after large one-day stock price movements, which are calculated by subtracting the normal return(s) from the actual return(s). The normal returns are calculated by using a variation of the Capital Asset Pricing Model (CAPM), which is based on Cox and Peterson (1994). The only difference is that they used the market model, while this study uses the CAPM to calculate the normal returns. This method contains one pre-event and one post-event estimation period. The pre-event alphas and betas are calculated over an estimation period of 105 to 6 trading days prior to the event date, while the post-event alphas and betas are calculated over an estimation period from 21 to 120 trading days after the event date. Subsequently, the average values of the pre- and post-event CAPM alpha and beta are used to calculate the normal returns. The average values are taken, since the results show that risk is not constant over time, which is in line with Chan (1988). A firm's beta, which proxies for systematic risk, increases substantially after large one-day stock price movements. One-day price declines or increases of at least 10% are characterized as events. The bid-ask spread proxies for transaction costs, the market capitalization for firm size, the daily trading volume for liquidity, the Baker and Wurgler (2007) Sentiment Index for investor sentiment and the CBOE Volatility Index (VIX) and (un)systematic risk for risk.

Prior studies already examined the overreaction hypothesis for the global financial crisis of 2008 (Tarchen, 2012), but limited research has been conducted on this hypothesis during the COVID-19 pandemic. Loang and Ahmad (2022) examined the short-term overreaction effect for the COVID-19 crisis. However, they failed to control for transaction costs, liquidity, investor sentiment and risk. Besides, they used another methodology than this paper does and made no split between value and growth firms as this paper does. Loang (2022) examined the impact of investor sentiment and market sentiment on overreaction in the European and US stock markets before and during the pandemic. However, they used other proxies for investor sentiment than this paper does and they did not control for transaction costs, firm size, liquidity and risk. Additionally, they conducted their research for NASDAQ companies rather than for NYSE companies as this paper does. Next to examining the overreaction hypothesis after having controlled for transaction costs, firm size, liquidity, investor sentiment and risk, this paper examines whether the short-term overreaction effect is driven by the difference between value and growth stocks. Since, academic literature did not take transaction costs, firm size, liquidity, investor sentiment, risk into account and made no distinction between value and growth stocks to explain the short-term price reversal during the COVID-19 pandemic in the US stock market, this paper contributes the existing literature significantly.

Consistent with existing literature, this study finds significant short-term price reversals after large stock price movements for both losers and winners. However, no evidence is found that greater initial price movements lead to bigger subsequent reversals. The price reversal is the most prevalent on the first trading day after the event for losers, while winners have a one-day delay and experience the largest reversal on the second trading day after the event. Losers only outperform winners in the first three trading days after the event, while winners outperform losers over the period of 4 to 20 trading days afterwards. Besides, this paper finds evidence that investors tend to undervalue value stocks and overvalue growth stocks, as investors may have the systematic tendency to project growth too far into the future and to undervalue the ability of struggling business to recover. Furthermore, the results of this paper show that for both loser and winner stocks the bid-ask bounce leads to larger price reversals, meaning that much of the short-term reversal is attributable to the bid-ask bounce. However, for both losers and winners, no evidence is found for the size effect, liquidity and investor sentiment to be explanatory for the short-term price reversal. Moreover, after removing the bid-ask bounce the size effect was even less prevalent. These results are consistent with Cox and Peterson (1994), who found that much of the reversal is attributable to the bid-ask bounce and that the size effect disappeared after removing the bid-ask bounce. Finally, the results of this study provide evidence for the risk-change effect, as it has been found that systematic risk for both losers and winners significantly leads to significantly higher cumulative abnormal returns. Consequently, this means that loser stocks with high systematic risk experience larger reversals, while winners experience smaller reversals. Additionally, the results of this paper show that systematic risk is not constant over time, which is in line with Chan (1988). Lastly, unsystematic risk is found to lead to significant smaller reversals for loser stocks and greater reversals for winner stocks.

The results of this paper have theoretical implications for the field of behavioral finance, stock markets and psychology and more notably for investor overreaction. The empirical evidence of this study can be relevant for investors, practitioners and academics to be aware of the existence of market overreaction during the COVID-19 pandemic and the determinants that could cause this phenomenon. Regular investors could benefit from this study, as the findings of this paper show investors that the contrarian investment strategy can be profitable during pandemics or other insecure times. However, this paper does not state that investors could profit consistently by performing the contrarian investment strategy, as the price reversal is not only explained by overreaction, but also by the bid-ask bounce and risk-change effect. Besides, regulators and policymakers will be able to better inform about the overreaction hypothesis. If they are more aware of the consequences of the overreaction hypothesis during turbulent financial times like the COVID-19 pandemic, they are able to better protect the stock markets for those kinds of anomalies.

The remainder of this paper is organized as followed. Firstly, Chapter 2 provides a literature review, in which the main findings of existing literature are presented. This section discusses the influence of COVID-19 on the US stock market, the price reversal effect, the differences between value and growth stocks and it states all the tested hypotheses. Chapter 3 provides information about the data collection and selection process and what kind of adjustments to the data are made. It also provides more insights about the data of the sample by enlightening the descriptive statistics. The next chapter explains what kind of event study is used and which methodology is used to test all hypotheses. Chapter 5 discusses the empirical findings of this study and concludes whether the hypotheses are being rejected or accepted. Finally, this paper concludes the main empirical findings, including the theoretical and practical implications of this results. Additionally, the limitations of this study and recommendations for future research are being discussed.

CHAPTER 2 Literature review and hypotheses development

This section discusses the main findings of the existing literature. Firstly, this section discusses how the US stock market was influenced by the COVID-19 pandemic. Secondly, this chapter provides information about the price reversal effect and its determinants proposed by existing literature. Thereafter, the difference between value and growth stocks is discussed. Lastly, this section states all the hypotheses that this paper examines.

2.1 The COVID-19 pandemic

No one could have thought about the consequences of the first confirmed COVID-19 case on 1 December 2019 in China. From then on, the virus spread in rapid pace across the globe. Three months after the first confirmed case, on 11 March 2020, the COVID-19 outbreak was proclaimed by the World Health Organization (WHO) to be officially a pandemic (WHO, 2020). According to WHO's Coronavirus Dashboard on 17 June 2023, there have been 768 million confirmed cases reported causing the deaths of almost 7 million people globally. Just recently on 5 May 2023 the WHO declared the pandemic to be officially over.

In order to slow down the spread and to alleviate the pressure on the healthcare systems, governments and other authorities implemented numerous restrictions. People were obliged to wear face masks, wash their hands and to go in quarantine and isolation when you had been in contact with an infected person (Güner, Hasanoğlu & Aktaş ,2020). Next to these personal protective measures, there were also some social measures which had an even greater impact on society. These measures included physical distancing, no more mass gatherings, travel bans resulting in closed borders, curfews and most countries also implemented lockdown procedures (Talic et al., 2021). Consequently, schools, catering establishments, sports clubs, non-governmental organizations (NGOs), offices and businesses had to close.

In light of the enormous impact of the COVID-19 virus on the physical and psychological health of the population, the economic and financial effects may seem secondary. However, at some point in time the economic and financial impacts became also paramount. All these restrictions had a great impact on economies and caused consumer consumption to decline significantly. Some industries, like aviation and hospitality, were even shut down completely. As a result, the stock markets were also heavily affected. Stock prices plummeted and market volatility soared worldwide (Baker et al., 2020). This section further discusses how the stock market was influenced by the COVID-19 pandemic.

2.1.1 Stock market crash

The stock market crash resulting from the COVID-19 outbreak was unique, as the world had never experienced a stock market crash caused by a similar event before. No previous infectious disease outbreak had impacted the U.S. stock market as heavily as COVID-19 (Baker et al., 2020). They stated that precedent pandemics just left small traces on the U.S. stock market. Just a few weeks before COVID-19 was considered to be a pandemic on 19 February 2020, the S&P 500 was on its all time high for that moment. One month later the index had dropped 34% due to the growing threat of the pandemic (Pisani, 2021).

Given the immense impact of the pandemic on US stock market performance, recent studies have begun to examine the effects of COVID-19. According to Mazur, Dang and Vega (2021), 90% of the stocks of the S&P 1500 reported large negative returns. They documented that petroleum, real estate, entertainment and hospitality were among the industries that were hit the hardest. Stock prices of firms in the petroleum industry plummeted on average 77% and hence was the worst performing sector. However, not all industries were impacted negatively by the pandemic. Sectors like healthcare and medical services, food and grocery distribution, software and technology and natural gas benefited significantly. These sectors all gained positive returns of more than 20%. Regarding US industrial returns during the pandemic, Baek, Mohanty and Glambosky (2020) and Goodell and Huynh (2020) found the same sectors to be negatively and positively affected by COVID-19. Similarly, Ramelli and Wagner (2020) observed the same effects for these industries in the two months before COVID-19 officially became a pandemic. Ashraf (2020) found that the S&P 500 return was negatively correlated with the number of confirmed COVID-19 cases in the first four months of 2020.

Based on existing literature, it can be concluded that the US economy, financial markets and most of the stocks suffered during the COVID-19 pandemic. Hence, the Federal Reserve (FED) implemented a 0% interest rate. Furthermore, on 15 March 2020, the FED launched a quantitative easing plan to acquire $500 billion in Treasury securities and $200 billion in mortgage-backed securities (Timiraos, 2020). Additionally, on 27 March 2020, President Trump immediately signed the Coronavirus Aid, Relief and Economic Security (CARES) Act into law after it had been enacted by the Congress with overwhelming support (Chen & Yeh, 2021). This economic relief package exceeded $2 trillion. The two latter showed that the US stock performance of most sectors recovered after the quantitative easing announcements. Besides, they observed that the sectors most affected by the pandemic benefited the most of the quantitative easing plans and that quantitative easing boosted investor confidence. According to Zhang, Hu and Ji (2020), these governmental interventions increased uncertainty and hence might create problems for in the long run. As uncertainty increased during the pandemic, the NYSE became more volatile and unpredictable.

2.1.2 Stock market volatility during COVID-19

As COVID-19 spread from a local crisis in China to a global pandemic, uncertainty and market volatility increased sharply worldwide since its outbreak. In the middle of March 2020 in the United States (US), volatility levels reached heights last seen in October 1987 and December 2008 and before that in late 1929 and early 1930s. By the end of March 2020, volatility levels started to recover and in the latter part of April 2020, declined significantly, while still remaining far above pre-pandemic levels (Baker et al., 2020). They argued that government restrictions on commercial activities and voluntary social distancing in a service-oriented economy were the main reasons for much higher volatility levels during COVID-19 in the US compared to previous pandemics, like the Spanish Flu. Zaremba, Kizys, Aharon and Demir (2020) found corresponding results. They concluded that government interventions increased the volatility in the international stock markets significantly and robustly. This growth in volatility was mainly driven by COVID-19 information campaigns and cancellations of public events.

Baek, Mohanty and Glambosky (2020) also agreed on the fact that COVID-19 had a significant impact on the US stock market volatility. They found a significant relationship for both negative and positive COVID-19 news on the US stock market volatility. Besides, they found that the market risk was not the same across industries. Firms operating in the petroleum and natural gas, restaurants, hotels and lodgings industries experienced large increases in risk. Mazur, Dang and Vega (2021) found similar results for these industries. They also showed that loser stocks had more asymmetric movements and exhibited extreme volatility that correlated negatively with stock returns in the US during March 2020.

Albulescu (2021) investigated the effect of official announcements regarding new confirmed COVID-19 cases and the fatality ratio on the stock market volatility in the US. He showed that COVID-19 amplified the US financial market volatility. Baig, Butt, Haroon and Rizvi (2021) and Engelhardt, Krause, Neukirchen and Posch (2021) found similar results. Both papers concluded that increases in confirmed COVID-19 cases and deaths resulted in a significant increase in US stock market volatility. On the other hand, Onali (2020) found no significant relationship between the announcements of COVID-19 cases and related deaths and the US stock market volatility. Yet, the majority of the existing literature documents a higher stock market volatility during the pandemic in the US.

2.2 Price reversal effect

As a result of the increased volatility, large one-day stock price movements were not uncommon during the COVID-19 pandemic in the NYSE. In their influential paper about the long-term effect of large one-day stock price movements, De Bondt and Thaler (1985) found that these are followed by substantial price reversals. This pattern is also referred to as the ‘price reversal effect’. The two defined stocks that experienced a large one-day price decrease as ‘loser’ stocks and stocks that experienced a large one-day price increase as ‘winner’ stocks. Subsequently, they constructed winner and loser portfolios over a 3-year period and found that loser portfolios gained almost 20% more than the market in the next three years, while the market gained roughly 5% more than winner portfolios in the three years after portfolio construction. As the loser portfolios outperformed the winner portfolios by almost 25%, they concluded that the price reversal effect is asymmetrical. Additionally, they concluded that the effect was most prevalent in the second and third year after portfolio formation. Furthermore, they found evidence for the ‘January effect’, since loser portfolios gained significantly large returns in January. This effect held till five years after portfolio formation. Chopra, Lakonishok and Ritter (1992) also examined the long-term price reversal effect and found similar results, even after controlling for firm size and beta. They constructed loser and winner portfolios over a 5-year period and concluded that loser portfolios outperformed winner portfolios by 5-10% per year during the five years after portfolio construction. Besides, their results provided evidence for the January effect.

Next to the long-term price reversal effect, the short-term effect is also documented thoroughly by existing literature. This short-term effect is examined by analysing the stock returns of the day(s) after a large one-day stock price movement. Using this method, Bremer and Sweeney (1991) observed that large negative daily stock returns are followed by positive rebounds over the following two days. The two used a trigger of -10% and found that the average day 1 abnormal return is 1.773%. By day 2, the average cumulative abnormal return was 2.215% meaning that the majority of this return was gained on the first day after the large one-day stock price decline. Their findings are robust and distinct from other anomalies like turn-of-the-year and weekend effects. Although, the results do not represent abnormal profit opportunities, these reversals raise questions about the duration of the price adjustment period. This long recovery period is inconsistent with the Efficient Market Hypothesis (EMH), which was introduced by Fama (1965). This theory states that in an efficient market current prices reflect all relevant and available information about the actual value of financial assets. Consequently, securities are always traded at their fair value and mispricings of assets should not persist in an efficient market. According to the EMH, it is impossible to ‘beat the market’ consistently by using information that is publicly available, as this is already incorporated in the stock prices. Cox and Peterson (1994) also investigated the price reversal effect following large one-day stock price declines. They did not find empirical evidence supporting short-term overreaction yielding profitable investment strategies, despite their significant reversals. In order to understand the price reversal effect, this section further discusses some explanations for this price reversal effect. Additionally, it discusses how regular investors could profit from these large stock price movements by using a contrarian investment strategy.

2.2.1 Overreaction hypothesis

As mentioned above, existing literature has found long-term and short-term price reversals after large preceding stock price movements. Prior studies found several possible explanations for this price reversal effect, but the most pronounced explanation is the ‘overreaction hypothesis’. The study of Kahneman and Tversky (1972) forms a foundation for explaining this behavioral bias. They argued that people overvalue the similarity of existing events when assessing the probability of another event to occur, which they referred to as the ‘representativeness heuristic. In reality, the overreaction hypothesis states that investors overvalue newly available public information and undervalue past information when they estimate the probability of the occurrence of future events. As a result, they overreact when unexpected news becomes public (De Bondt & Thaler, 1985). When applying this overreaction hypothesis to the stock market, this phenomenon causes stocks to be overvalued after receiving good news and undervalued after receiving bad news.

De Bondt and Thaler (1985) inspired most other research on the long-term overreaction effects. Chopra, Lakonishok and Ritter (1992) elaborated on the study of De Bondt and Thaler (1985) and found similar results after controlling for firm size and systematic risk. Stock (1990) also conducted research on the long-term overreaction effect and, consistently with De Bondt and Thaler (1985), found the same winner-loser anomaly for the German stock market. Additionally, he documented that the overreaction effects decreased when shortening the underlying periods. His robust findings suggest no violation of the efficient market hypothesis. Furthermore, Alonso and Rubio (1990) found empirical evidence for the long-term overreaction effect for the Spanish market. Papers examining the long-term overreaction in various other countries, such as Brazil (da Costa, 1994), Germany (Meyer, 1994; Mun, Vasconcellos & Kish, 1999; Schiereck, De Bondt & Weber, 1999), United Kingdom (UK) (Clare & Thomas, 1995) and Baytas and Cakici (1999) for Canada, France, Germany, Italy, Japan, UK and US, all showed that the long-term overreaction effect is persistent after controlling for firm size and arithmetical errors (Conrad & Kaul, 1993). In their large-scale global study, Blackburn and Cakici (2017) examined the long-term overreaction for 23 developed countries divided into four geographical clusters, which are North America, Europe, Japan and Asia. Similar to De Bondt and Thaler (1985), they found economically and statistically significant stock price returns from buying preceding long-term losers and selling preceding long-term winners. This result held for the set of all stocks in the clusters of North America, Japan and Asia, but not for Europe. Although the latter study found no significant price reversal effect in Europe, it can be concluded that the long-term overreaction effect is not a one-hit phenomenon, but that it is observed worldwide.

Many other studies also attributed the overreaction hypothesis being the reason of short-term price reversals. In the first study about the short-term overreaction effects on the US stock market, Arbel and Jaggi (1982) did not find significant results for stocks that were put on the Wall Street Journal's Winner-Loser list. Atkins and Dyl (1990) used the same methodology and observed that loser stocks significantly gained positive abnormal returns on average, while winners significantly earned negative abnormal returns in the US. Bremer and Sweeney (1991) only examined price drops in the US stock market and were the first ones to use an absolute daily trigger of -10% to define event days. They found evidence for the price reversal effect by observing an average abnormal return of 1.773% for the first day after an event and a cumulative abnormal return of 2.215% after the second day. Similarly, Cox and Peterson (1994) also observed significant reversals after large daily price drops. Ma, Tang and Hasan (2005) documented overreaction with a more pronounced effect for losers than for winners in the US. However, Larson and Madura (2003) found that US stock market was too optimistic rather than overreacting. They observed negative abnormal returns for losers and winners. Ising, Schiereck, Simpson and Thomas (2006) observed the same results for the German market.

Existing literature also documented the short-term overreaction effects outside the US. Otchere and Chan (2003) found empirical evidence of short-term overreaction in the Hong Kong market. However, they observed that the overreaction phenomenon was more pronounced for winner stocks than for loser stocks. Additionally, after controlling for transaction costs, their results became economically insignificant meaning that Hong Kong's stock market is efficient in the weak form of the EMH. Similarly, Akhigbe, Gosnell and Harikumar (1998) found the same for the US stock market after controlling for transaction costs. Pham, Nguyen and Tô (2007) also documented evidence for the short-term overreaction effect in Vietnamese, Japanese and Australian stock markets and also found results supportive for the weak form of the EMH. Lobe and Rieks (2011) conducted research on the short-term overreaction effect in the German stock market and found evidence supporting this phenomenon. Additionally, they observed that the absolute values of abnormal returns after price decreases were larger than those after price increases, which is consistent with the finding of De Bondt and Thaler (1985). Other studies also documented the short-term overreaction for countries, such as China (Wang, Burton, & Power, 2004), Greece (Antoniou, Galariotis & Spyrou, 2005), New Zealand (Bowman & Iverson, 1998), Turkey (Vardar & Okan, 2008) and Ukraine (Plastun & Mynhardt, 2013). Given the findings of existing literature, it can be said that the short-term overreaction effect also is a global phenomenon.

The opposite effect of the overreaction phenomenon does also exist and is called 'underreaction'. This theory states that news is slowly incorporated into stock prices causing prices to continue moving in the direction of the initial price change, which is also referred to as the 'continuation effect'. Hong and Stein (2002) found empirical evidence of a short-term underreaction effect and observed that this effect is more pronounced for small and low-analyst-coverage stocks in the US stock market. Similarly, Pritamani and Singal (2001), also observed short-term underreaction effects for the US stock market. However, after controlling for transaction costs, the underreaction effect became unexploitable. Jegadeesh and Titman (1993) showed that a strategy of buying stocks that had performed well and selling stocks that had performed poorly generated significant positive abnormal returns over holding periods of 3 to 12 months, which supports a long-term underreaction effect. After controlling for systematic risk and delayed stock price reactions to common factors, their results remained significant. Neither Pritamani and Singal (2001) nor Larson and Madura (2003), who also provided evidence for the underreaction phenomenon, found firm size to be influential on the reaction to price shocks. Stock (1990) showed results supporting underreaction for the German stock market.

2.2.2 Other possible explanations

After the publication of De Bondt and Thaler (1985), many studies found the overreaction hypothesis being the cause of the price reversal effect. However, numerous extensions of the research of De Bondt and Thaler (1985) were conducted in order to examine whether this price reversal could be explained by other factors. This section discusses five other possible explanations for the short-term price reversal effect.

The bid-ask bounce

Numerous studies (Conrad & Kaul, 1993; Cox & Peterson, 1994; Conrad, Gultekin & Kaul 1997; Akhigbe, Gosnell & Harikumar 1998) considered the bid-ask bounce to explain overreaction. They argued that large daily price drops are likely to be related to considerable selling pressure. Consequently, there is a higher chance that a closing transaction will occur at the bid price. This, in turn, can trigger reversals the following day due to the bid-ask bounce, resulting in spurious negative serial correlation in stock returns. Similarly, for large daily increases, the heightened buying pressure raises the likelihood of a closing transaction occurring at the ask price, which because of the bid-ask bounce will cause the reversal the following day. However, Bharati, Crain and Nanisetty (2009), who used US data, found no evidence supporting the bid-ask bounce. Similarly, Choi and Jayaraman (2009) also rejected the bid-ask bounce as an explanation for overreaction. A possible explanation for this contradiction in literature could be the decline in bid-ask spread over time, which was observed by He and Wu (2003) for the US stock market. They found that bid-ask spreads declined significantly due to a reduction in market making costs and an increase in competition for order flows after reforms of the US stock market in 1997. De Fontnouvelle, Fishe and Harris (2003) also found smaller bid-ask spreads as a result of more competition.

The size effect

The second possible explanation states that the overreaction is a manifestation of firm size. Zarowin (1990), using US data, replicated the study of De Bondt and Thaler (1985) and concluded that the anomaly of short-term overreaction remained after controlling for firm size. However, he showed that the tendency for losers to outperform winners in the long run is not because of the overreaction hypothesis, but because of the losers being smaller-sized firms than the winners. This theory is also referred to as the 'size effect' and states that companies with a low market capitalization outperform companies with a high market capitalization. It was established by Banz (1981) when he observed that on average small firms had significantly larger risk adjusted returns than large firms for the US stock market over a period of forty years. Similarly, Chopra, Lakonishok and Ritter (1992) and Ma, Tang and Hasan (2005) concluded that firm size reduced the abnormal returns for losers in the US market. Cox and Peterson (1994) also found proof for the size effect, but after removing the bid-ask bounce this effect disappeared. On the other hand, in a succeeding study, De Bondt and Thaler (1987) showed additional evidence that supports the overreaction hypothesis and is inconsistent with the size effect. Alonso and Rubio found supporting evidence and confirmed that the overreaction hypothesis cannot be rejected after controlling for firm size, which only partly explains profitability. Besides, Blackburn and Cakici (2017) did not find support for a global size effect in their study that examined the long-term reversal pattern in the stock markets of 23 developed countries. Thus, there is some contradiction in existing literature regarding the size effect.

Liquidity

Another possible explanation that might explains the short-term overreaction effect is the degree of market liquidity. Cox and Peterson (1994) examined the role of market liquidity in explaining the short-term price reversal effect. They found that larger price reversals should happen in less liquid marketplaces, when transitory liquidity plays a significant role in price reversals. They also argued that reversals should weaken over time as markets become more liquid due to an increase in traders and decreased transaction costs. According to Cox and Peterson (1994), market liquidity is partially responsible for the short-term price reversal effect. Similarly, Bremer and Sweeney (1991), argued that market illiquidity partially explains the short-term price reversal effect. Lasfer, Melnik and Thomas (2003) and Butt, Högholm, and Sadaqat (2021) found that the reversal effect is more pronounced for less liquid equities. Furthermore, Campbell, Grossman and Wang (1993) showed that investors who provide liquidity after large stock price movements in order to meet the selling or buying pressure, will earn excess returns. They argued it to be the right reward for supplying liquidity in unsecure and turbulent times, in which the risk attitude of many investors shifts.

Investor sentiment

Piccoli and Chaudhury (2018) examined another behavioral explanation where the state of investor sentiment drives investor reaction to large stock price movements. Extreme market fluctuations are by construction low likelihood events. When these events occur, they violate common expectation and arouse the emotion of 'surprise' (Meyer, Reisenzein & Schützwohl, 1997; Reisenzein, 2000). This causes overestimation of the incidence (Griffin & Tversky, 1992; Spohr, 2014; Choi & Hui, 2014; Payne, Browning & Kalenkoski, 2016) and thus overreaction. However, investors tend to overreact stronger during periods of low sentiment, because they perceive extreme market events as being in greater contrast to their prior belief (Teigen & Keren, 2003). Meaning that when sentiment is low, investors are more perturbed by unusually large stock price movements, believing that their prior belief was grossly mistaken. Hence, Piccoli and Chaudhury (2018) concluded that individuals tend to overreact economically and statistically significantly more during low investor sentiment periods rather than high sentiment periods. Hence, price reversals tend to be larger in times of low investor sentiment.

Risk-change effect

The last possible explanation for stock market overreaction is the risk-change effect. Vermaelen and Verstringe (1986) re-examined the study of De Bondt and Thaler (1985) for the Belgian stock market and also found empirical evidence for overreaction. However, they argued that this overreaction effect is a rational market response to changes in risk. Their 'risk-change hypothesis' claims that a decrease (increase) in stock prices leads to an increase (decrease) in debt-equity ratios and consequently an increase (decrease) in risk as measured by CAPM betas. In other words, it states that during the test period losers are riskier than winners and hence losers are rewarded with higher expected returns (De Bondt & Thaler, 1987). Similarly, Ball and Kothari (1989) showed that the betas of extreme losers exceeded those of extreme winners by 0.76 in the period after portfolio formation. Supporting this risk-change effect, Chan (1988) observed in the US stock market for both loser and winner stocks that a firm's beta, which proxies for ‘systematic risk’, is not constant over time and changes after large one-day stock prices. After controlling for risk changes, he found only small abnormal returns. Furthermore, McLean (2010) found that for the US market price reversals are prevalent only in high unsystematic risk stocks. Meaning that both systematic and unsystematic risk are of importance for explaining overreaction. However, De Bondt and Thaler (1987) rejected this risk-change effect in their follow-up study. As their arbitrage portfolio had a positive beta of 0.220, this was insufficient to explain their average annual (test period) return of 9.2%. Besides, their analysis showed that the arbitrage portfolio had a negative beta in down markets and a positive one in up markets, which cannot be considered as particularly risky.

2.2.3 Contrarian investment strategy

As mentioned above, existing literature has shown empirical evidence of the price reversal effect, which is caused by investor overreaction. This gives rational arbitrageurs the opportunity to exploit these mispricings. As winners tend to be overvalued and losers undervalued according to the overreaction hypothesis (Chan, 1988), arbitrageurs could make substantial profits by buying loser stocks and shorting winner stocks. This investment strategy is also referred to as the ‘contrarian investment strategy’. This section discusses the main findings existing literature has documented so far and describes the opposite investment strategy of the contrarian investment strategy.

Existing literature has thoroughly documented that buying past losers and selling past winners consistently leads to substantial profits (De Bondt & Thaler, 1985; Shefrin & Statman, 1985; De Long, Shleifer, Summers & Waldmann, 1990; Lehmann, 1990). Even after controlling for plausible levels of transactions costs, this strategy remained profitable (Lehmann, 1990; Jegadeesh, 1990). Similarly, Ma, Tang and Hasan (2005) found that a contrarian investment strategy generated a 4.5% cumulative abnormal return during a two-day period in the US stock market for NYSE firms. They also argued that transaction costs need to be taken into account, but showed that the returns were high enough to cover these. Using US stock market data, Chan (1988) examined whether the contrarian investment strategy generates abnormal returns. His methodology was slightly different compared to other previous research, as he controlled for changes in risk. He found that the risks of losers and winners were not constant over time. After controlling for these risk changes, he found only small contrarian abnormal returns. Additionally, he argued that the expected market-risk premium is correlated with the risk of employing the contrarian investment strategy. Hence, the magnitude of the (cumulative) abnormal returns is affected by the way risk is measured. Jegadeesh and Titman (1995) showed that the contrarian profit can be attributed to both overreaction and the lead-lag effect. However, they observed that the majority of contrarian profit is obtained because of stock price overreaction and that a small part of the profit can be attributed to the lead-lag effect. Similarly, in their study on the profitability of the contrarian investment strategy, Lo and MacKinlay (1990) stated that overreaction is not the only determinant of contrarian profits. They concluded that just less than 50% can be attributed to investor overreaction, while the majority of contrarian profits is because of the lead-lag effect, which means that returns on stocks systematically lead or lag those of others. Additionally, they found that the stock returns of larger firms lead those of smaller firms. Conrad, Gultekin and Kaul (1997), found at their turn that contrarian profits are largely attributable to the bid-ask bounce in transaction prices. Controlling for this almost eliminated all profits and any remaining profit disappeared after taking transaction costs into account.

According to the underreaction hypothesis, which is the opposite of the overreaction hypothesis, newly public information is slowly incorporated into stock prices and as a result stock prices continue to move in the same direction as the initial stock price movement. The investment strategy to gain abnormal return from this continuation effect is also referred to as the 'momentum strategy'. Underreaction means that the momentum traders can profit by trend-chasing (Hong & Stein, 2002). In other words, this strategy entails buying past winners and shorting past losers. After controlling for systematic risk and delayed stock price reactions to common factors, Jegadeesh and Titman (1993) found empirical evidence supporting this theory by showing that for the US market this strategy generated significant abnormal returns over holding periods from 3 to 12 months. Additionally, they observed that these abnormal returns declined significantly after the first year after portfolio formation. Supporting the momentum strategy, Chan, Jegadeesh and Lakonishok (1996), who used US data, concluded that the market's response to news takes time. Profitable momentum strategies have also been observed outside the US. Hudson, Keasey and Littler (2001) and Mazouz, Joseph and Joulmer (2009) documented evidence for this investment strategy to be profitable in the UK market. In his study of 12 European countries, Rouwenhorst (1998) concluded that an internationally diversified portfolio of past winners outperformed a portfolio of past losers by roughly 1% per month. Additionally, he found that the continuation effect held for all countries and for both small and large firms, while the effect was stronger for small firms. His European evidence is quite similar to the findings for the US market of Jegadeesh and Titman (1993), suggesting that this US evidence was not a one-hit observation. However, Hong and Stein (2002) found that if momentum traders in the US can only implement univariate investment strategies, their attempts at arbitrage must inevitably cause overreaction in the long run. Forner and Marhuenda (2003) showed similar results for the Spanish stock market. In their study on investment strategies in the US stock market, Plastun, Sibande, Gupta and Wohar (2021) found that during and after the financial crisis of 2008 the contrarian investment strategy was profitable, while a momentum strategy was profitable before the crisis. They mentioned that crisis periods can be a possible explanation for this evolution.

2.2.4 Value versus growth stocks

According to Fama and French (1998) there can be made a distinction between value and growth stocks in the stock market. Firms with low market equity to book (M/B), price to earnings (P/E) and price to cash (P/C) ratios are considered as value stocks and firms with high ratios as growth stocks. In their study where they examined the returns of value and growth stocks for the US and 12 other developed EAFE (Europe, Australia and the Far East) countries, they concluded that value stocks outperformed growth stocks over the long run and suggested that firm size may proxy for risk. In twelve of the thirteen markets, value stocks had higher returns than growth stocks. Average returns on global portfolios of low and high M/B stocks differed by 7.68% per year. When sorting for P/E or P/C they found similar value premiums. By showing that value stocks outperform growth stocks, Fama and French (1998) implicitly suggested that value stocks are undervalued and growth stocks overvalued. In a previous study, where they introduced the three-factor model, which includes a value factor, Fama and French (1992) found empirical evidence that value stocks have higher expected returns than growth stocks in the US stock market, which also implicitly states that growth stocks might be overvalued and value stocks undervalued. Similarly, Stattman (1980) and Barr Rosenberg and Lanstein (1998) showed that value stocks on average outperform growth stocks in the US stock market. Besides, Asness, Moskowitz and Pedersen (2013) indirectly supported the theory of value stocks being undervalued by providing evidence that value stocks outperform growth stocks for the US, UK, continental European and Japanese stock markets. Rozeff and Zaman (2002) went one step further and stated that regular investors overvalue growth stocks and undervalue value stocks in their research on the US stock market. However, existing literature does not have a clear explanation for this effect. Supporting this finding, Haugen (1995) argued that outside investors may have a systematic tendency to project growth too far into the future and to undervalue the ability of struggling business to recover. Similarly, Lakonishok, Shleifer and Vishny (1994) found that investors tend to overreact to recent performance and extrapolate this into the future, causing investors to overvalue growth stocks and undervalue value stocks. This behavioral bias is also referred to as the 'extrapolation bias' and states that people tend to overvalue recent events when making decisions about the future. Given all findings in existing literature, it can be concluded that regular investors have the tendency to overvalue growth stocks and undervalue value stocks.

2.3 Hypotheses development

Existing literature has thoroughly provided evidence of a short-term price reversal effect after large one-day stock price movements (e.g., Kahneman & Tversky, 1972; De Bondt & Thaler, 1985; Bremer & Sweeney, 1991; Cox & Peterson, 1994). Since the US stock market volatility soared during the pandemic, it is plausible that similar results also hold for the US stock market during the COVID-19 pandemic. Therefor, this paper examines the following two hypotheses:

H1: A large one-day stock price decrease is followed by a significant short-term price reversal during the COVID-19 pandemic.

H2: A large one-day stock price increase is followed by a significant short-term price reversal during the COVID-19 pandemic.

Kahneman and Tversky (1979) introduced the term 'loss aversion', which means that people's response to losses is stronger than the response to gains of the same size. This indicates that people value losses over corresponding gains. The findings of De Bondt and Thaler (1987) and Alonso and Rubio (1990), Zarowin (1990) and Clare and Thomas (1995) all correspond with this loss aversion theory. All the papers found that loser stocks outperform winner stocks. Hence, the following alternative hypothesis is tested in this study:

H3: The short-term price reversal after large one-day stock price movements is significantly larger for loser stocks than for winner stocks during the COVID-19 pandemic.

According to Fama and French (1998), there can be made a distinction between value and growth stocks in the stock market. Firms with low market equity to book (M/B), price to earnings (P/E) and price to cash (P/C) ratios are considered as value stocks, while firms with high ratios are considered as growth stocks. Rozeff and Zaman (2002) stated that regular investors overvalue growth stocks and undervalue value stocks. Although Lakonishok, Shleifer and Vishny (1994) and Haugen (1995) argued similar findings, existing literature does not have a clear explanation for this phenomenon. Hence, it is important to further investigate this effect. As this research assumes the stock market to be efficient (EMH), it is expected that these mispricings are corrected for. This paper expects the short-term price reversal to be significantly larger for value stocks after large stock price drops and significantly larger for growth stocks after large stock price increases. Therefor, the following two alternative hypotheses are tested whether these hold:

H4: The short-term price reversal effect after large one-day stock price decreases is significantly larger for value stocks than for growth stocks during the COVID-19 pandemic.

H5: The short-term price reversal effect after large one-day stock price increases is significantly larger for growth stocks than for value stocks during the COVID-19 pandemic.

As discussed in Chapter 2.2.2, existing literature proposes a few other possible explanations for the short-term price reversal effect. Among them are the bid-ask bounce, size-effect, liquidity, investor sentiment and risk-change effect. Hence, it is of great importance to control for these factors and to look whether they have a significant impact on the short-term price reversal effect. Therefor, the following six alternative hypotheses are tested in this study:

H6: The short-term price reversal effect after large one-day stock price movements is significantly impacted by transaction costs during the COVID-19 pandemic.

H7: The short-term price reversal effect after large one-day stock price movements is significantly impacted by firm size during the COVID-19 pandemic.

H8: The short-term price reversal effect after large one-day stock price movements is significantly impacted by liquidity during the COVID-19 pandemic.

H9: The short-term price reversal effect after large one-day stock price movements is significantly impacted by investor sentiment during the COVID-19 pandemic.

H10: The short-term price reversal effect after large one-day stock price movements is significantly impacted by systematic risk during the COVID-19 pandemic.

H11: The short-term price reversal effect after large one-day stock price movements is significantly impacted by unsystematic risk during the COVID-19 pandemic.

CHAPTER 3 Data

In this section the data selection and collection process are being discussed. This section describes several selection criteria and when events are excluded. Additionally, this chapter discusses the descriptive statistics of the data to provide more insights on the distributions of all the used variables.

3.1 Data collection and selection

The research period of this paper is from 11/03/2020 to 30/06/2022. The research period starts at 11/03/2020 because on this day the WHO declared the COVID-19 outbreak to be officially a pandemic. Due to a lack of data regarding the Sentiment Index of Baker and Wurgler (2007), the end date of the research period is 30/06/2022. Initially 05/05/2023 was considered as the end date, since that day the WHO declared the pandemic to be over. Luckily, the period that now has been excluded is at the end of the pandemic. As most COVID-19 restrictions were already abolished then, this has a limited impact on the outcome of this research. After removing the holidays there remained a total of 582 trading days for this research period.

This study uses the New York Stock Exchange (NYSE) as index for its dataset, since the NYSE is the largest stock exchange in the world and therefor a good representation of the economy as a whole. Besides, most academic papers use the NYSE for their dataset as well. Hence the results of this research can be easier compared to the results of existing literature. The daily closing ($P_{i,t}$), bid ($PB_{i,t}$) and ask ($PA_{i,t}$) prices of all companies listed on the New York Stock Exchange (NYSE) are collected from the Eikon - Datastream database for all trading days during the period from 09/10/2019 till 20/12/2022. Due to the estimation periods, which are being discussed in Chapter 4, this period does not match the research period. Additionally, all the Standard Industrial Classification (SIC) codes of all NYSE companies are retrieved from the Eikon – Datastream database. The daily closing prices are used to calculate the daily stock price returns by using the following formula:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} * 100\%,$$

where $R_{i,t}$ represents the return of stock i on time t. The daily stock price returns are compared to a trigger of -10% or 10%, which is similar to the approach of Bremer and Sweeney (1991) and Cox and Peterson (1994). A stock price return smaller than -10% or greater than 10% is defined as an event. As volatility levels increased significantly since the outbreak of COVID-19 (Baker et al., 2020), is might also be interesting to look at extremer trigger values. Hence this study also looks at triggers of -20% and -15% for losers and 15% and 20% for winners as a robustness check. When an event has one estimation period that is covered by less than 60% of daily stock price returns during this estimation window, this event is eliminated from the sample, which is consistent with Ma, Tang and Hasan (2005). Additionally, events with stock prices less than $1,- one trading day before the event are also excluded, as price oscillation between the bid and ask prices may cause the short-term price reversal for loser stocks with low share prices (Bremer & Sweeney, 1991; Cox & Peterson, 1994). They stated that this might be because stock prices are often expressed in whole dollars and eights. However, back in the nineties, decimal pricing had not yet been adopted in the US stock market. This occurred in 2000, when the Securities and Exchange Commission (SEC) introduced decimal trading, which resulted in narrower bid-ask spreads (Ip, 2000). Hence, this research uses a threshold of $1,- instead of $10,-, like Bremer and Sweeney (1991) and Cox and Peterson (1994), as the reporting of stock prices in this dataset is more accurate.

This paper uses a similar approach as Fama and French (1998) to make a distinction between value and growth stocks and uses the market-to-book (M/B) ratio as indicator to make this distinction. The data regarding this M/B ratio are obtained from the Eikon - Datastream database. They defined value stocks as stocks whose M/B ratio is among the lowest 30% and growth stocks as stocks whose M/B ratio is among the highest 30% of a country. A dummy variable is used to distinguish value and growth stocks and equals 1 if a stock is considered as a value stock and 0 if a stock is considered as a growth stock. Fama and French (1998) made this distinction at the end of each calendar year. Hence this study does the same and makes a total of three distinctions, namely for 2020, 2021 and 2022. This method only uses 60% of the stocks, so in order to have a value for this dummy variable at each event, only firms within the bottom or top 30% are selected each year. As there are three different distinctions and it is likely that the composition of the bottom and top 30% changes during these three years, it means that there are three different stock portfolios out of which events can occur each year. In total there are 1,529 different NYSE companies selected by this method out of a total of 1,941. Per year there are 583, which equals 30% of 1,941, loser and winner stocks selected, meaning that annually 1,166 different companies are selected either as loser or winner stock.

Just two events (one negative and one positive stock price movement) per day are selected to minimize across-sample correlation. This resulted in 537 observations for losers and 568 for winners. Both samples still have observations close to the maximum of 582, which is the total number of trading days during the research period. This means that the methodology regarding the dummy variable for value stocks does not have a large impact on the total number of observations per sample. Similar to Ma, Tang and Hasan (2005), events with the most extreme (negatively or positively) price movement are selected on multi-event days. Besides, only one event per company is selected, which also minimizes across-sample correlation, to prevent event periods from the same company to overlap. If the most extreme price movement on a certain date is from a company that has already been selected, the second most extreme value is selected, and so on until a value is found of a company that has not already been selected. If there is just one event that is already selected or in case of multiple events on a particular date and all of them have already been selected, the event with the most extreme value of which the estimation period does not overlap with the estimation window of another event of the same company is selected. This is done to avoid multicollinearity and as a result, there are no events of the same company within the same estimation period. An event is removed from the sample if it could not meet all the criteria mentioned above. After applying these selection criteria, there remained 466 observations for loser stocks and 528 for winner stocks and hence a total of 994.

In order to calculate the Cumulative Abnormal Return, the dependent variable, and the Abnormal Return at the event date, one of the independent variables, the returns of the New York Stock Exchange Composite (NYA) and the risk-free rate are also needed next to the returns of all NYSE companies, as this study uses the CAPM. Hence, the closing prices of the NYA are collected from Yahoo Finance for the same period as the NYSE stock prices in order to calculate the NYA returns, which is done by the same formula used for the NYSE returns. In this paper the 10-year average of the 90-day US Treasury bill rate is used as the risk-free rate. This is consistent with Bruner, Eades, Harris and Higgins (1998), who stated that most practitioners choose between the 90-day Treasury bill rate and a long-term Treasury bond with a maturity exceeding ten years as the risk-free rate. As they mentioned that the risk-free rate should correspond to the tenor of the cash flows being valued, it is most appropriate to use the 90-day US Treasury bill rate. The 10-year average is taken, since the rate has fluctuated substantially over the past few years. The data regarding the risk-free rate are obtained via https://home.treasury.gov/resource-center/data-chart-center/interest-rates/TextView?type=daily_treasury_bill_rates&field_tdr_date_value=2023, which is the website of the US Department of Treasury. More details about the CAR and AR calculations can be found in Chapter 4.

As numerous studies (Conrad & Kaul, 1993; Cox & Peterson, 1994; Conrad, Gultekin & Kaul 1997; Akhigbe, Gosnell & Harikumar 1998) considered the bid-ask bounce to explain overreaction, this study controls for the bid-ask spread on the day of the event. Existing literature argued that large daily price drops are likely to be related to considerable selling pressure. As a result, there is a higher chance that the bid price will be used in a closing transaction. Due to the bid-ask bounce, this might then result in reversals the next day and a fictitious negative serial correlation in stock returns. Similarly, for large daily increases, the heightened buying pressure raises the likelihood of a closing transaction occurring at the ask price, which because of the bid-ask bounce will cause the reversal the following day. According to Demsetz (1968), the bid-ask spread is one of the two variables that covers almost all of transaction costs. The other one they consider is brokerage fees. Hence, in this paper the bid-ask spread is used as a proxy to control for transaction costs. The following formula is used to calculate the bid-ask spread for stock i on time t:

$$BA_{i,t} = \frac{PA_{i,t} - PB_{i,t}}{PA_{i,t}} * 100\%,$$

where $BA_{i,t}$ represents the bid-ask spread for stock i on time t. The data regarding the bid and ask prices are obtained from the Eikon – Datastream database.

This paper controls for the size of a company by using the natural logarithm of the market capitalization of each company, as existing literature found firm size to also partially explain the short-term price reversal effect (e.g., Zarowin, 1990; Chopra, Lakonishok & Ritter, 1992; Cox & Peterson, 1994). The natural logarithm is taken rather than the regular value of this variable to make the data more normally distributed, since the data of this variable were moderately skewed. In this way outliers have less impact on the results. The data regarding the market capitalization are gathered from the Eikon - Datastream database. The market capitalization 5 trading days before the event date is taken instead of the market capitalization on the event date, as using the market capitalization on the event date might result in multicollinearity. As the stock price return on the event date is directly related to the market capitalization on the event date, this will likely cause multicollinearity. Market capitalization is measured in millions of dollars.

Besides, this study uses the daily trading volume of each NYSE stock as a proxy for liquidity, since existing literature concluded market liquidity to have a significant impact on the short-term reversal effect (e.g., Bremer & Sweeney, 1991; Cox & Peterson, 1994; Lasfer, Melnik & Thomas, 2003; Zawadowski, Andor & Kertész, 2006; Butt, Högholm & Sadaqat, 2021). The data regarding liquidity are gathered from the Eikon - Datastream database. As the magnitude of trading volume can differ significantly between different stocks, the natural logarithm of this variable is used. By doing so, outliers have less impact on the results. This variable is measured in millions of traded shares.

Since Piccoli and Chaudhury (2018) found evidence that showed that investors tend to overreact more in periods of low investor sentiment, this paper also controls for investor sentiment. The data regarding investor sentiment are gathered from Baker and Wurgler (2007), which can be collected from http://www.stern.nyu.edu/~jwurgler. They defined a Sentiment Index based on five indicators that represent investor sentiment. The five characteristics comprise the value-weighted dividend premium defined following Baker and Wurgler (2004); the closed-end fund discount from Morningstar; the number and first-day returns on IPOs from Ibbotson, Sindelar and Ritter (1994) and the equity share in new issues defined following Baker and Wurgler (2000). Originally, the index was based on six proxies, but the trading volume as measured by NYSE turnover has been dropped as one of the indicators. Turnover does not mean what it once did, given the migration of trading to a variety of venues and the explosion of institutional high-frequency trading. The higher the value of the index, the higher the optimism. Since this index is only available by month and an event can happen at any day during this month, this paper calculates a weighted average of the index based on the current and next month. This study uses the same approach as that of Piccoli and Chaudhury (2018). This research divides each calendar month into six intervals of roughly 5 days. The weight changes from 100% of the current month and 0% of the next month in the first interval to 0% of the current month and 100% of the next month in the sixth interval by steps of 20% in both directions. As this index is only available until June 2022, the end of the research period is 30/06/2022.

Lastly, in this research several variables control for risk. One of the proxies for risk is the CBOE Volatility

Index (VIX). The data regarding this volatility index can be retrieved from the CBOE website via https://www.cboe.com/tradable_products/vix/vix_historical_data/. This index is one of the most recognized measurements of expected equity volatility and benchmarks of volatility. The index indicates the degree or expected level of uncertainty in the stock market, which means the VIX index is a forward looking indicator of market volatility. Specifically, the VIX index measures the 30-day expected volatility of the S&P 500 by using CBOE listed options on the S&P 500 as input. Higher values of the index suggest more expected uncertainty being priced into the stock market, while lower values indicate less expected uncertainty. Although this volatility index uses the S&P 500 rather than the NYSE as input, it is still a reliable indictor for risk for stocks of the NYSE. Furthermore, this paper also controls for systematic and unsystematic risk, since existing literature (Vermaelen and Verstringe, 1986; Chan, 1988; Ball and Kothari, 1989; McLean, 2010) found support for the risk-change effect and concluded that both systematic and unsystematic risk are of importance for explaining overreaction. This effect states that during the test period losers are riskier than winners and hence losers are rewarded with higher expected returns (De Bondt & Thaler, 1987). The beta of the pre-event estimation period serves as a proxy for systematic risk. This type of risk refers to the risk that is inherent to the entire market or specific industry, reflecting the impact of economic, geopolitical and financial factors. It affects the overall market rather than it is firm-specific. The average error term of the pre-event estimation period proxies for unsystematic risk. This type of risk refers to risk that is not shared with a wider market or industry and is also known as the root mean square error. Both systematic and unsystematic risk are being estimated by means of the CAPM.

3.2 Descriptive statistics

Table 1 shows the descriptive statistics after winsorizing for loser stocks (Panel A) and winner stocks (Panel B), using triggers of -10% and 10% respectively. To restrict the undesired impact of extreme outliers, the returns at the event date of losers are winsorized at the 1st percentile, while those of winners are winsorized at the 99th percentile. As loser events only occur from -10% or less there is not winsorized at the 99th percentile. The opposite holds for winner stocks. Additionally, the variables AR(0), AR(1), AR(2), AR(3), CAR(1,3), CAR(1,20) and CAR(4,20) are winsorized at the 1st and 99th percentile. Many outliers of these variables were clustered at the same event, resulting in only losing 14 observations for both samples, resulting in 452 observations for losers and 514 for winners. Before winsorizing, some of the kurtoses of these winsorized variables had values exceeding 150 and far beyond, which means there were some extreme outliers that influenced the results significantly. Hence, winsorizing for these variables was necessary.

When you observe the number of observations for extremer triggers in Table 2, it makes sense that the average return at the event date of winners substantially differs more from its trigger value than the average of losers, which can be seen in Table 1. Hence, it is not surprising that Table 1 shows that the mean of CAR(-5,20) for losers (-11.8%) is closer to its corresponding trigger than the mean of CAR(-5,20) for winners (23.1%). Additionally, the mean CAR(-5,20) for losers and winners shows that it is seriously impacted by the return at the event date, since the mean for losers is negative and the mean for winners positive. Additionally, the descriptive statistics table shows that the mean CAR(1,3) and CAR(1,20) for losers are approximately 1.5% and 0.1% respectively, which means that on average a price reversal effect is observed for 1 to 20 trading days after large stock price decreases. However, this result does not hold for the CAR of 4 to 20 trading days after the event, as this average is negative, which supports the momentum strategy. On the other hand, the average CAR(1,3), CAR(1,20) and CAR(4, 20) values for winners all show negative values, which supports short-term overreaction. The average cumulative abnormal return of winners for 1 to 20 trading days after the event even is around -2.1%. The bid-ask spread is on average

Table 1: Descriptive statistics

Notes: This table presents the descriptive statistics of the sample for loser stocks (Panel A) and winner stocks (Panel B) separately over the research period from 11/03/2020 till 30/06/2022. N corresponds to the total number of events determined by a trigger strategy that uses -10% for losers and 10% for winners as triggers. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The bid-ask spread is determined on the event date. For the variables market capitalization (measured in USD millions) and trading volume (measured in millions of stocks) the natural logarithm is used to restrict the impact of outliers. While trading volume is determined for the event date, is the market capitalization obtained 5 trading days before the event. The investor sentiment is based on the Sentiment Index of Baker and Wurgler (2007). The CBOE volatility index represents the 30-day expected level of uncertainty in the stock market. Alpha represents the excess return of a stock relative to what is predicted by the CAPM, while beta measures the systematic risk of a stock, not to be confused with unsystematic risk.

Panel A. Loser stocks								
Variable	**N**	**Mean**	**Min**	**Median**	**Max**	**Std. Dev**	**Skewness**	**Kurtosis**
Return at event date	452	-0.188	-0.578	-0.164	-0.101	0.082	-1.763	6.511
CAR(-5,20)	452	-0.118	-1.185	-0.148	1.366	0.348	0.603	5.639
AR(0)	452	-0.186	-0.505	-0.168	-0.065	0.079	-1.467	5.216
AR(1)	452	0.008	-0.438	-0.001	0.722	0.098	1.612	13.533
AR(2)	452	0.006	-0.551	0.000	0.503	0.081	0.850	14.624
AR(3)	452	0.001	-0.254	-0.004	0.538	0.076	2.011	14.785
CAR(1,3)	452	0.015	-0.528	0.001	0.755	0.139	0.970	7.815
CAR(1,20)	452	0.001	-0.956	-0.009	0.993	0.265	0.344	5.253
CAR(4,20)	452	-0.014	-0.935	-0.019	1.061	0.233	0.550	6.120
Bid-ask spread	452	0.005	0.000	0.001	0.134	0.013	5.534	41.480
Market capitalization	452	6.787	1.065	6.690	13.481	1.898	0.199	2.885
Trading volume	452	7.663	0.531	7.957	11.991	2.109	-0.647	3.410
Investor sentiment	452	0.918	0.016	1.071	2.083	0.624	-0.052	1.672
CBOE volatility index	452	26.066	15.010	24.030	82.690	9.843	2.530	11.852
Pre-event alpha	452	0.001	-0.014	0.000	0.034	0.006	1.281	6.736
Post-event alpha	452	0.000	-0.018	0.000	0.026	0.005	0.566	6.077
Pre-event beta	452	1.384	0.121	1.256	4.279	0.831	0.508	2.797
Post-event beta	452	1.594	0.126	1.530	7.543	0.926	1.472	9.870
Pre-event unsystematic risk	452	0.052	0.002	0.046	0.256	0.029	2.146	12.088
Post-event unsystematic risk	452	0.051	0.011	0.045	0.293	0.031	3.556	22.974

Panel B. Winner stocks								
Variable	**N**	**Mean**	**Min**	**Median**	**Max**	**Std. Dev**	**Skewness**	**Kurtosis**
Return at event date	514	0.244	0.100	0.198	0.893	0.143	1.903	7.231
CAR(-5,20)	514	0.231	-0.844	0.191	2.391	0.355	0.954	6.888
AR(0)	514	0.240	0.075	0.197	0.894	0.141	1.867	7.182
AR(1)	514	0.000	-0.323	-0.011	0.888	0.112	3.041	20.990
AR(2)	514	-0.006	-0.294	-0.007	0.372	0.075	0.447	6.808
AR(3)	514	0.001	-0.241	-0.003	0.501	0.071	1.092	9.298
CAR(1,3)	514	-0.005	-0.459	-0.013	0.615	0.136	0.826	6.458
CAR(1,20)	514	-0.021	-0.909	-0.023	1.105	0.274	0.635	5.543
CAR(4,20)	514	-0.017	-0.757	-0.023	1.151	0.232	0.954	6.674
Bid-ask spread	514	0.006	0.000	0.002	0.125	0.013	4.580	29.479
Market capitalization	514	6.398	0.610	6.254	12.393	1.881	0.292	3.091
Trading volume	514	7.842	-1.204	7.903	13.267	2.100	-0.371	3.577
Investor sentiment	514	0.919	0.016	1.116	2.083	0.623	-0.058	1.671
CBOE volatility index	514	25.503	15.010	23.290	82.690	9.526	2.607	12.588
Pre-event alpha	514	0.000	-0.018	0.000	0.024	0.005	0.146	4.798
Post-event alpha	514	0.001	-0.017	0.000	0.066	0.006	3.357	33.329
Pre-event beta	514	1.324	0.121	1.267	3.594	0.760	0.387	2.657
Post-event beta	514	1.522	0.122	1.449	4.496	0.868	0.585	3.118
Pre-event unsystematic risk	514	0.049	0.002	0.045	0.259	0.026	1.746	10.923
Post-event unsystematic risk	514	0.048	0.000	0.043	0.329	0.028	3.780	30.474

0.5% for losers and 0.6% for winners, which differs significantly from the average bid-ask spread (4.4%) of Cox and Peterson (1994). This difference supports the findings of He and Wu (2003), who found that bid-ask spreads declined significantly over time due to a reduction in market making costs and an increase in competition for order flows after reforms of the US stock market in 1998. Furthermore, it can be seen in Table 1 that the pre- and post-event alpha for losers and winners almost stay the same, while the pre- and post-event betas for both losers and winners substantially increase. This means that firms become riskier in terms of systematic risk after large stock price movements, which supports the findings of Chan (1988), who observed that the systematic risk of losers and winners is not constant over time in the US stock market. Additionally, Table 1 shows that the mean pre-event beta of losers (1.384) is slightly larger than the mean of winners (1.324), which is consistent with Vermaelen and Verstringe (1986) and Ball and Kothari (1989). However, the difference between the two average values is way smaller than the difference Ball and Kothari (1989) observed. Lastly, Table 1 shows that for both losers and winners the level of unsystematic risk stays almost the same, which means that the risk-change effect is mainly driven by a change in systematic risk.

In Table 2 the average values of the (cumulative) abnormal returns of losers and winners for extremer triggers can be observed. It can be seen that the CAR(-5,20) of losers for all triggers is negative on average, while the average CAR(-5,20) of winners for all triggers is positive. This shows that the return at the event date has a substantial impact on this variable. The average CAR(1,3) of losers for all triggers is positive and the mean CAR(1,3) of winners is negative for the triggers of 10% and 15%, which supports a short-term price reversal for the period of 1 to 3 trading days after the event. For winners this price reversal also seems to hold for the periods of 1 to 20 and 4 to 20 trading days after the event, while for losers this price reversal only further holds for the CAR(1,20). However, no conclusions can be drawn from this table, since no tests of significance have been conducted yet for these variables. Additionally, Figure 1 presents the development of the price levels of the NYA over the research period plus estimation periods. A clear price drop can be observed in March 2020, when the WHO declared the COVID-19 outbreak to officially be a pandemic. By the beginning of 2021, the NYA already reached its pre-pandemic price level again.

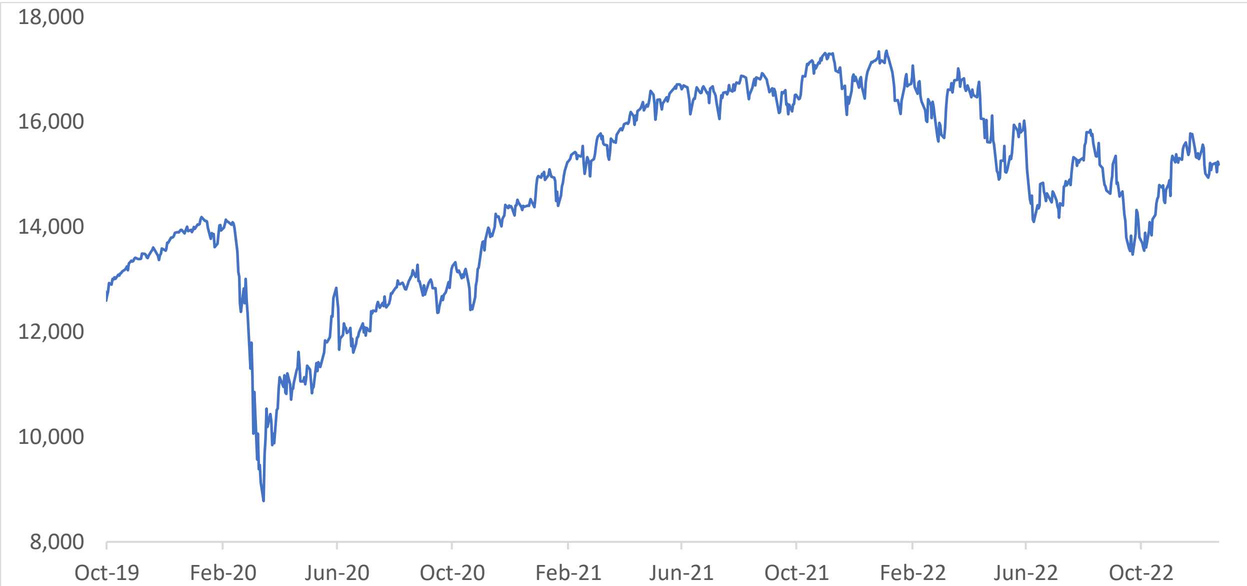
Table 2: The average (Cumulative) Abnormal Return for different trigger values

Notes: This table presents the average values of the (cumulative) abnormal returns following large stock price movements over the research period from 11/03/2020 till 30/06/2022 for different triggers. The CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date.

	Loser stocks			**Winner stocks**		
	-20%	**-15%**	**-10%**	**10%**	**15%**	**20%**
Variable	**n = 193**	**n = 317**	**n = 452**	**n = 514**	**n = 413**	**n = 383**
Return at event date	-28.533%	-23.419%	-18.823%	24.390%	28.633%	35.141%
CAR(-5,20)	-14.714%	-12.951%	-11.780%	23.060%	28.161%	26.227%
AR(0)	-27.739%	-22.939%	-18.580%	24.037%	28.195%	24.551%
AR(1)	1.892%	0.642%	0.835%	0.000%	0.268%	0.926%
AR(2)	0.037%	0.507%	0.569%	-0.606%	-0.582%	-0.489%
AR(3)	0.148%	-0.183%	0.130%	0.149%	0.185%	0.100%
CAR(1,3)	2.077%	0.966%	1.534%	-0.457%	-0.129%	0.537%
CAR(1,20)	1.948%	1.210%	0.122%	-2.120%	-1.283%	0.514%
CAR(4,20)	-0.129%	0.245%	-1.412%	-1.663%	-1.154%	-0.024%

Figure 1: The trading levels of the New York Stock Exchange Composite (NYA)

Notes: This figure shows the rate of the NYA for the research period including both estimation periods.



Chapter 4 Methodology

This chapter discusses the methodology used in this research. Firstly, the type of event study and all its details are discussed. Additionally, the statistical tests that are being used to test the first three hypotheses are being explained. Besides, this chapter discusses the regression models this research uses to test the last eight hypotheses. Lastly, it discusses which fixed effects are being included and which are not and which statistical tests are included to deal with heteroskedasticity and multicollinearity. The methodology of this study is mainly based on the academic papers of Cox and Peterson (1994) and Ma, Tang, and Hasan (2005).

4.1 Event study

This study uses an event study in order to test all eleven hypotheses, which is a statistical method to see what the impact of a certain event is on a particular variable or parameter. This statistical method was established by Fama, Fisher, and Roll (1969). Daily stock price returns less than -10% or greater than 10% are used in this paper as indicators for an event. However, as a robustness check this paper also looks at extremer trigger values. As this research examines the short-term price reversal effect, this study makes use of the AR rather than the Buy and Hold Abnormal Return (BHAR), which is used for long-term event studies. The AR is the difference between the actual return and the expected/normal return of a security. The normal returns are calculated by using a variation of the CAPM, which is based on Cox and Peterson (1994). The only difference is that they used the market model, while this study uses the CAPM to calculate the normal returns. This method contains one pre-event and one post-event estimation period. The pre-event alphas and betas are calculated over an estimation period of 105 to 6 trading days prior to the event date, while the post-event alphas and betas are calculated over an estimation period from 21 to 120 trading days after the event date. The following formula is used to calculate these CAPM parameters:

$$R_{i,t} = \alpha_i + r_f + \beta_i(R_{m,t} - r_f) + \varepsilon_{i,t},$$

with the assumption that:

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

where $R_{i,t}$ represents the return of stock i at time t, r_f the risk-free rate, α_i (alpha) the excess return of stock i relative to what is predicted by the CAPM, β_i (beta) the systematic risk of stock i, $R_{m,t}$ the return of the market (NYA) at time t and $\varepsilon_{i,t}$ the error term, which is assumed to be normally distributed. The average error term is considered to be representing the unsystematic risk. Subsequently, the average values of the pre- and post-event CAPM alpha and beta are used to calculate the normal returns. The average values are taken, since Chapter 3.2 shows that risk is not constant over time, which is consistent with Chan (1988). A firm's beta, which proxies for systematic risk, increases substantially after large one-day stock price movements for both losers and winners. Hence, it is not clear what an appropriate estimation period is. The ARs for all eleven hypotheses are then calculated using the following formula:

$$AR_{i,t} = R_{i,t} - \left(\bar{\alpha}_i + r_f + \bar{\beta}_i(R_{m,t} - r_f\right),$$

where $AR_{i,t}$ represents the abnormal return of stock i at time t, $\bar{\alpha}_i$ the average of the pre- and post-event alpha and $\bar{\beta}$ the average of the pre- and post-event beta. In order to calculate the Cumulative Abnormal Return (CAR) the underlying formula is used:

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

where $CAR_{i,t}$ is the cumulative abnormal return of stock i at time t. The largest event window in this paper contains 26 trading days and is an event window of 5 days prior to 20 days after the event. Additionally, this study makes CAR calculations for an event period of 1 to 3 trading days after the event, 1 to 20 trading days after the event and 4 to 20 trading days after the event, which all is consistent with Cox and Peterson (1994). Since this research examines the short-term price reversal effect, the CAR is not calculated for trading days after 20 trading days following the event date.

4.2 Statistical tests

This section discusses the methodologies that are used to test the first three hypotheses of this research. These hypotheses are all being tested by conducting different kind of t-tests. Each statistical test is conducted separately for all mentioned event windows for all the six trigger values. The first two hypotheses are tested by means of multiple one-tailed, one-sample t-tests, while the third hypothesis is tested by means of multiple one-tailed, two-sample t-tests. The specific methodologies per hypothesis are discussed below.

Hypothesis 1

The first hypothesis tests whether a large one-day stock price decrease is followed by a significant short-term price reversal during the COVID-19 pandemic. This hypothesis is only tested for loser stocks by using multiple one-tailed one-sample t-tests. In total 18 different one-tailed one-sample t-tests are conducted to answer the first hypothesis. The AR of 1, 2 and 3 trading days after the event and the CAR of 1 to 3, 1 to 20 and 4 to 20 trading days after the event are used as the event periods for this test. For all these six event periods the one-tailed one-sample t-test is tested for all three negative triggers (-20%, -15% and -10%). Since this hypothesis tests a price reversal effect after large one-day stock price decreases, the 18 different t-tests tests if the (C)AR is significantly larger than 0. This one-tailed one-sample t-test uses the average (C)AR of all 18 subgroups to test whether it is significantly greater than zero. Hence, if the following equation holds, the first hypothesis can be accepted:

$$(C)AR_{loser,t} > 0,$$

where $(C)AR_{loser,t}$ is the (cumulative) abnormal return for loser stocks and t is one of the six event periods.

Hypothesis 2

The second hypothesis tests whether a large one-day stock price increase is followed by a significant short-term price reversal during the COVID-19 pandemic. This hypothesis is tested only for winner stocks by also using multiple one-tailed, one-sample t-tests. Again, 18 different one-tailed one-sample t-tests are performed in order to test the second hypothesis. The same six event periods as the first hypothesis are used to test this hypothesis. However, this time the price reversal effect is tested for all three positive triggers (10%, 15% and 20%). As a price reversal effect is expected, these 18 t-tests test if the (C)AR is significantly smaller than zero. Again, this one-tailed one-sample t-test uses the average (C)AR of all 18 subgroups in order to test whether it is significantly smaller than 0. The following equation needs to hold to accept the second hypothesis:

$$(C)AR_{winner,t} < 0,$$

where $(C)AR_{winner,t}$ is the (cumulative) abnormal return for winner stocks and t is one of the six event periods.

Hypothesis 3

The third hypothesis tests whether the short-term price reversal after large one-day stock price movements is significantly larger for loser stocks than for winner stocks during the COVID-19 pandemic. This hypothesis is tested by using a one-tailed two-sample t-test and needs the (C)ARs of both losers and winners to compare the short-term price reversal between losers and winners. Similar to the first two hypotheses, this hypothesis again is tested by 18 different t-tests, which all test whether the (C)AR of losers is significantly larger than the (C)AR of winners. This one-tailed two-sample t-test uses the average (C)AR of loser and winner stocks to test whether the (C)AR of loser stocks is significantly greater than the (C)AR of winner stocks. The difference between the (C)AR of losers and winners needs to be significantly larger than zero. However, as a price reversal is expected, the $(C)AR_{loser,t}$ is assumed to be positive, while the $(C)AR_{winner,t}$ is expected to be negative. This means that the signs of both variables are in the opposite direction. Hence, the following equation, needs to hold to accept the third hypothesis:

$$(C)AR_{loser,t} + (C)AR_{winner,t} > 0$$

The difference between the two variables now becomes larger if the $(C)AR_{winner,t}$ is also positive and the difference becomes smaller if the $(C)AR_{winner,t}$ is indeed negative. By simply comparing the absolute (cumulative) abnormal returns of losers and winners, there cannot be (cumulative) abnormal returns in the opposite direction of the price reversal. For example, if a loser stock experiences a negative (cumulative) abnormal return, which is not a price reversal, this negative return is transformed into a positive (cumulative) abnormal return when using the absolute (cumulative) abnormal returns to test whether the reversal is larger for losers than for winners. For all 18 t-tests, a variance-comparison test has been conduced to check whether the variances of losers and winners are significantly different. For all the 18 tests, the variances differed significantly at the 1% level. Hence, Welch's approximation is used for all 18 t-tests to ensure more robust and reliable results (Welch, 1938).

4.3 Regression models

In this section, the methodology of hypotheses 4 to 11 are being discussed. The last eight hypotheses are tested by means of multiple different OLS regressions with the CAR as dependent variable, following Cox and Peterson (1994) and Ma, Tang and Hasan (2005). The regressions are performed for three different event periods of the dependent variable, which are the periods of 1 to 3, 1 to 20 and 4 to 20 trading days after the event date. Since the effect of some independent variables is strongly related with the effect of other variables, several interaction variables are included. Furthermore, the ARs of the event date are included in order to examine the relationship between this variable and the CARs of the trading days after the event. The multiple OLS regressions differ in the independent and control variables they use, but they have the same dependent variable (CAR). All the variables that are being used in the different regression models are defined as follows:

- CAR_i The Cumulative Abnormal Return for stock i for the three different event windows
- AR_i The Abnormal Return for stock i on the event date
- D_{loser} A dummy variable that is equal to 1 if the stock is a loser and 0 if the stock is a winner
- D_{value} A dummy variable that is equal to 1 if the stock is a value stock and 0 if the stock is a growth stock
- BA_i The bid-ask spread for stock i on the event date
- MC_i The natural logarithm of the market capitalization for stock i 5 days prior to the event date
- TV_i The natural logarithm of the trading volume for stock i on the event date
- IS_i Investor sentiment for stock i on the event date
- VI_i The CBOE Volatility Index for stock i on the event date
- SR_i The systematic risk of the pre-event estimation period for stock i based on the pre-event CAPM beta
- UR_i The unsystematic risk of the pre-event estimation period for stock i based on the pre-event average error term estimated by the CAPM
- ε_i The error term for stock i

In order to test hypotheses 4 and 5 only one regression model has been conducted. This model excludes the dummy variable D_{loser}, as hypothesis 4 is only tested for loser stocks and hypothesis 5 only for winner stocks. The specific methodologies for hypotheses 4 and 5 are specified below and the following OLS regression model is being used to test both hypotheses:

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{value} + \beta_3 BA_i + \beta_4 MC_i + \beta_5 TV_i + \beta_6 IS_i + \beta_7 VI_i + \beta_8 SR_i + \beta_9 UR_i + \varepsilon_i$$

Hypothesis 4

The fourth hypothesis tests whether the short-term price reversal effect after large one-day stock price decreases is significantly larger for value stocks than for growth stocks during the COVID-19 pandemic. Since this hypothesis only focuses on large stock price decreases, only large stock price movements of loser stocks are being taking into account. This hypothesis is tested separately for all three event periods of the CAR for all three negative triggers. The variable of interest for this hypothesis is the dummy variable D_{value}, which is equal to 1 for value stocks and 0 for growth stocks. As larger cumulative abnormal returns mean larger price reversals for losers, the fourth hypothesis can be accepted if the coefficient of this dummy variable is significantly larger than zero.

Hypothesis 5

The fifth hypothesis states that the short-term price reversal effect after large one-day stock price increases is significantly larger for growth stocks than for value stocks during the COVID-19 pandemic. As this hypothesis only looks at large stock price increases, only large stock price movements of winner stocks are being included. Again, this hypothesis is tested separately for the three CAR event periods mentioned above, but this time for the three positive triggers. The variable of interest for this hypothesis is again the dummy variable D_{value}, which is equal to 1 for value stocks and 0 for growth stocks. Since smaller cumulative abnormal returns mean larger price reversals for winners, the fifth hypothesis can be accepted if the coefficient of this dummy variable is significantly smaller than zero.

In order to test hypotheses 6 to 9, three different OLS regression models are being used. The first two regression models are tested for a sample that includes both losers and winners. Hence, the dummy variable D_{loser} has been included. The first regression model for hypotheses 6 to 9 is the following:

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 BA_i + \beta_5 MC_i + \beta_6 TV_i + \beta_7 IS_i + \beta_8 VI_i + \beta_9 SR_i + \beta_{10} UR_i + \varepsilon_i$$

In the second regression model to test hypotheses 6 to 9, an interaction term between D_{loser} and D_{value} (D_{loser} * D_{value}) has been added. This variable has been added to further examine the difference between loser and winner stocks. The second regression model to test hypotheses 6 to 9 is the following:

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} SR_i + \beta_{11} UR_i + \varepsilon_i$$

The third regression model that is used to test hypotheses 6 to 9 has been conducted separately for loser and winner stocks. Hence, the same regression model as for hypotheses 4 and 5 is used as the third model for hypotheses 6 to 9. This last model functions as a sanity check to see whether the results are the same, when the hypotheses are tested separately for losers and winners. The specific methodologies for hypotheses 6 to 9 are specified below.

Hypothesis 6

The sixth hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by transaction costs during the COVID-19 pandemic. The variable of interest for this hypothesis is the bid-ask spread (BA_i), which is used as a proxy for transaction costs in this study. This hypothesis is tested for all three CAR event periods and has been conducted for a sample that includes both losers and winners and has been conducted separately for losers and winners. The sixth hypothesis can be accepted if the coefficient of the variable of interest significantly differs from zero, meaning that the bid-ask bounce significantly impacts the short-term price reversal effect after large one-day stock price movements.

Hypothesis 7

The seventh hypothesis states that the short-term price reversal effect after large one-day stock price movements is significantly impacted by firm size during the COVID-19 pandemic. The variable of interest to test this hypothesis is the natural logarithm of the market capitalization five days prior to the event (MC_i), which is used as a proxy for firm size. Similarly, the hypothesis is tested for all three CAR event periods for a sample that includes both losers and winners and for losers and winners separately. The seventh hypothesis can be accepted if the coefficient of MC_i significantly differs from zero, meaning that the size-effect significantly impacts the short-term price reversal effect after large one-day stock price movements. For the seventh hypothesis an additional regression has been conducted to examine whether the size effect disappears after removing the bid-ask bounce, as this was found by Cox and Peterson (1994). This additional regression can be found in Table 10, which can be found in the Appendix.

Hypothesis 8

The eighth hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by liquidity during the COVID-19 pandemic. The independent variable to look at for this hypothesis is the natural logarithm of the daily trading volume at the event date (TV_i), which is used as a proxy for liquidity in this research. The hypothesis is also tested for all three CAR event windows and has been conducted for a sample that includes both losers and winners and for losers and winners separately. The eighth hypothesis can be accepted if the coefficient of TV_i is significantly different from zero, meaning that liquidity has a significant impact on the short-term price reversal effect after large one-day stock price movements.

Hypothesis 9

The ninth hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by investor sentiment during the COVID-19 pandemic. The independent variable to look at for this hypothesis is the investor sentiment (IS_i). Again, this hypothesis is tested for all three CAR event periods and has been conducted for a sample that includes both losers and winners and for losers and winners separately. The ninth hypothesis can be accepted if the coefficient of IS_i is significantly different from zero, meaning that investor sentiment has a significant impact on the short-term price reversal effect after large one-day stock price movements.

In order to test the last two hypotheses, five additional regression models are being performed. The first two regression models only apply to hypothesis 10, the third and fourth model only to hypothesis 11 and the last model applies to both hypotheses. The effect of systematic and unsystematic risk on the CAR is firstly examined separately as these two variables are highly correlated. For both types of risk, the interaction term with D_{loser} is included, since the effect of these variable is strongly related with each other. Additionally, for both types of risk there is a model that contains the interaction term with D_{value} for the same reason. The complete regression model that includes both types of risk can be found in the last equation. The five OLS regression models abovementioned are the following:

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} SR_i \beta_{11}(D_{loser} * SR_i) + \varepsilon_i$$

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} SR_i \beta_{11}(D_{loser} * SR_i) + \beta_{12}(D_{value} * SR_i) + \varepsilon_i$$

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} UR_i \beta_{11}(D_{loser} * UR_i) + \varepsilon_i$$

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} UR_i \beta_{11}(D_{loser} * UR_i) + \beta_{12}(D_{value} * UR_i) + \varepsilon_i$$

$$CAR_i = \alpha_i + \beta_1 AR_i + \beta_2 D_{loser} + \beta_3 D_{value} + \beta_4 (D_{loser} * D_{value}) + \beta_5 BA_i + \beta_6 MC_i + \beta_7 TV_i + \beta_8 IS_i + \beta_9 VI_i + \beta_{10} SR_i + \beta_{11}(D_{loser} * SR_i) + \beta_{12}(D_{value} * SR_i) + \beta_{13} UR_i + \beta_{14}(D_{loser} * UR_i) + \beta_{15}(D_{value} * UR_i) + \varepsilon_i$$

Hypothesis 10

The tenth hypothesis states that the short-term price reversal effect after large one-day stock price movements is significantly impacted by systematic risk during the COVID-19 pandemic. The variable of interest is the systematic risk of the pre-event estimation period, (SR_i), which is the pre-event CAPM beta. The systematic risk is also known as the overall market risk. The hypothesis is tested for the three CAR event windows and includes both winner and loser stocks. The tenth hypothesis can be accepted if the coefficient of SR_i significantly differs from zero, meaning that systematic risk significantly impacts the short-term price reversal effect after large one-day stock price movements.

Hypothesis 11

The last hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by unsystematic risk during the COVID-19 pandemic. The independent variable to look at for this hypothesis is the unsystematic risk of the pre-event estimation period (UR_i), which is the pre-event average error term estimated by the CAPM. Unsystematic risk is also known as firm-specific risk. Similarly, the hypothesis is tested for all three event windows including both winners and losers. The eleventh hypothesis can be accepted if the coefficient of UR_i is significantly different from zero, meaning that unsystematic risk has a significant impact on the short-term price reversal effect after large one-day stock price movements.

Allison (2009) stated that regression models that include fixed effects can account for time-invariant variables. Fixed effects are incorporated into regression models to control for the potential impact of differences in, for example, time, industry, geography or within firms, aiming to deal with potential endogeneity. This study includes year and industry fixed effects to tackle this potential endogeneity problem. However, this research excludes firm fixed effects, since most firms only have one observation in the sample.

Ensuring reliable regression results, this paper has conducted numerous statistical tests. In order to check for linearity in the regression models, the Ramsey RESET test is executed. This test tests whether the dependent variable is explained by non-linear combinations of the independent variables, which is crucial for an effective analysis (Ramsey, 1969). For none of the regression models, significant p-values are found, which means that for all of them linearity is found. Besides, the Shapiro-Wilk test is performed in order to test whether the residuals are normally distributed. This test is suitable for smaller sample sizes and checks whether the skewness and kurtosis of the residuals match those anticipated under the assumption of a normal distribution (Shaphiro & Wilk, 1965). The test statistics show values close to 1, which means that the residuals are close to be perfectly normally distributed. However, the t-statistics are not statistically significant. Thirdly, the Breusch-Pagan (Breusch & Pagan, 1979) and White (White, 1980) tests are executed to control for heteroskedasticity, which means constant variance of residuals across various levels of the independent variables. The results of the two statistical tests show evidence for the presence of heteroskedasticity in most of the regression models. Hence, all regressions are performed with robust standard errors to be consistent. Fourthly, this paper tests for autocorrelation within the residuals by conducting the Durbin-Watson (Durbin & Watson, 1950; 1951; 1971) and the Breusch-Godfrey (Breusch & Godfrey, 1981) tests. The first one is used for detecting first-order autocorrelation, while the second test for higher-order autocorrelation. The results of both statistical tests indicate that there is found no evidence of autocorrelation within the residuals. Lastly, this research calculates the Variation Inflation Factors (VIFs) to examine how much of an independent variable's variance might be accounted for by other independent variables, which is also known as multicollinearity. The VIF measures the multicollinearity's impact on an estimated coefficient's variance. Multicollinearity could lead to reduced test statistics, skewed signs and incorrect magnitudes of estimated coefficients. According to Brooks (2008), VIFs cannot exceed a value of 10 in order to execute a regression analyse. This threshold was not exceeded in this research, hence all the regression models could be conducted.

CHAPTER 5 Results

This chapter discusses and interprets the results of all the tested hypotheses. Firstly, the results of the one-tailed one-sample and two-sample t-tests are shown. These t-tests are performed to answer the first three hypotheses. Secondly, the results of the different regression models are discussed, which are used to answer hypotheses 4 to 11.

5.1 Short-term price reversals after large one-day stock price movements

Hypothesis 1

Panel A of Table 3 presents the (cumulative) abnormal returns of loser stocks and the corresponding t-statistics, which indicate whether the (cumulative) abnormal returns are significantly larger than zero. It can be seen that except for the abnormal return on the third trading day after the event for the -15% trigger, all abnormal returns are positive, which supports the short-term price reversal effect after large stock price decreases. Consistent with Bremer and Sweeney (1991), the largest reversal occurs on average on the first trading day after the event and for the -20% and -10% triggers this reversal even is statistically significant. This means that they are statistically significantly larger than zero. For the -20% trigger, this reversal even is almost 1.9%. It is not surprising that the largest reversal can be observed at the -20% trigger. This is consistent with the overreaction hypothesis, which states that a greater magnitude of the initial price change leads to a greater price reversal. The reversal is still prevalent on the second and third day, but the reversal effect is significantly less prevalent for these days. Given that almost all abnormal returns are positive for loser stocks, it is not surprising that the cumulative abnormal returns of 1 to 3 trading days after the event date for losers are also positive for all three triggers. Again, for the -20% and -10% triggers, this effect is statistically significant, which means that loser stocks tend to experience a short-term price reversal during the first three trading days after a large price drop. This corresponds with the findings of Bremer and Sweeney (1991). All average cumulative abnormal returns of 1 to 20 trading days after the event are also positive, supporting a short-term price reversal. However, none of them is statistically significant. The short-term price reversal is not or less prevalent for the average cumulative abnormal returns of 4 to 20 trading days after the event. This means that the short-term price reversal after large one-day stock price decreases is mainly driven by the abnormal returns of the first three days after the large price drop. Thus, the first hypothesis, which states that a large one-day stock price decrease is followed by a significant short-term price reversal during the COVID-19 pandemic, can only be accepted for the cumulative abnormal returns of 1 to 3 trading days after the event for the -20% and -10% triggers.

Hypothesis 2

Panel B of Table 3 shows the (cumulative) abnormal returns of winner stocks and its corresponding t-statistics. However, this time the t-statistics indicate whether the (cumulative) abnormal returns are significantly smaller than zero. It can be seen that on the first trading day after a large stock price increase no price reversal is observed, as the mean values for all three triggers are positive. However, the average abnormal returns of the second trading day after the event date do show negative values and are statistically significant for all three triggers. Hence, it seems that winners experience a one-day delay in the price reversal compared to loser stocks. Again, the largest reversal can be observed at the most extreme trigger, which is consistent with the overreaction hypothesis. Since the average abnormal return of the third trading day after the event date is positive again for all three triggers, the cumulative abnormal return of 1 to 3 trading days after the event date is for none of the triggers statistically significant smaller than zero. The sign of this cumulative abnormal return is even positive for the 20% trigger, which supports a short-term continuation effect. On the other hand, the cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event date are negative for all three triggers. Moreover, the average cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event date are statistically significant for the 10% trigger. Given the small price reversal in the first three days after the event date, the short-term price reversal after large stock price increases is mainly driven by the cumulative abnormal return of 4 to 20 trading days after the event date. Thus, the second hypothesis, stating that a large one-day stock price increase is followed by a significant short-term price reversal during the COVID-19 pandemic, can only be accepted for the cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event for the 10% trigger.

Table 3: The (Cumulative) Abnormal Returns after large one-day stock price movements

Notes: This table presents the average (cumulative) abnormal returns after large one-day stock price movements over the period from 11/03/2020 till 30/062022 and the corresponding one-tailed one-sample t-statistics in brackets. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period ranges from 105 to 6 days prior to the event, while the post-event estimation period ranges from 21 to 120 days after the event date. The (cumulative) abnormal returns of loser stocks are tested to be significantly larger than zero, while those of winners to be significantly smaller than zero. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

	Panel A. Loser stocks			**Panel B. Winner stocks**		
	-20%	**-15%**	**-10%**	**10%**	**15%**	**20%**
(C)AR	**n = 193**	**n = 317**	**n = 452**	**n = 514**	**n = 413**	**n = 383**
AR(1)	1.892%*	0.642%	0.835%*	0.000%	0.268%	0.926%
	[1.849]	[1.026]	[1.843]	[0.000]	[0.436]	[1.252]
AR(2)	0.037%	0.507%	0.569%	-0.606%*	-0.787**	-0.818%*
	[0.052]	[0.920]	[1.511]	[-1.860]	[-1.994]	[-1.842]
AR(3)	0.148%	-0.183%	0.130%	0.149%	0.185%	0.100%
	[0.218]	[-0.401]	[0.370]	[0.482]	[0.498]	[0.257]
CAR(1,3)	2.077%*	0.966%	1.534%**	-0.457%	-0.334%	0.248%
	[1.663]	[1.147]	[2.388]	[-0.771]	[-0.461]	[0.293]
CAR(1,20)	1.948%	1.210%	0.122%	-2.120%*	-1.942%	-0.436%
	[0.841]	[0.691]	[0.099]	[-1.777]	[-1.343]	[-0.289]
CAR(4,20)	-0.129%	0.245%	-1.412%	-1.663%*	-1.608%	-0.684%
	[-0.063]	[0.158]	[-1.305]	[-1.649]	[-1.305]	[-0.552]

Hypothesis 3

Table 4 presents the differences in the average (cumulative) abnormal returns after large stock price movements between loser and winner stocks and the corresponding t-statistics. Since the signs of the triggers for losers and winners are in the opposite direction, the absolute trigger values are used to compare both. So, the -10% is compared with the 10% trigger for example. Moreover, as the short-term price reversal effect expects a positive (cumulative) abnormal return for losers and negative (cumulative) abnormal returns for winners, the signs of the (cumulative) abnormal returns are also expected to be different. The one-tailed two-sample t-tests that are presented in Table 4 therefor test whether the (cumulative) abnormal return of losers plus the (cumulative) abnormal return of winners is significantly larger than zero. This table shows that on the first trading day after the event loser stocks experience a substantially larger price reversal than winners. For a trigger of 20%, this effect even is significant at the 5% level. However, on the second trading day after the event, the effect is the other way around, which means that winner stocks experience a greater price reversal on the second day. This is consistent with Akhigbe, Gosnell and Harikumar (1998), who also found the short-term price reversal to be slightly delayed for winners. However, existing literature

Table 4: The differences in average (Cumulative) Abnormal Returns between loser and winner stocks

Notes: This table shows the differences in average (cumulative) abnormal returns between loser and winner stocks over the period of 11/03/2020 till 30/06/2022 and the corresponding one-tailed two-sample t-statistics. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The absolute trigger values are compared to examine the difference, as the signs of the triggers for losers and winners are different. Since the signs of the (cumulative) abnormal returns for losers and winners are also expected to be in the opposite direction, the following is tested: $(C)AR_{loser,t} + (C)AR_{winner,t} > 0$. This refers to testing whether the difference between the (cumulative) abnormal return of losers and winners is significantly larger than zero, given the opposite signs of the variables. Hence, a positive value means that losers experienced a greater price reversal than winners and vice versa. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

(C)AR	**10%**	**15%**	**20%**
AR(1)	0.835%	0.910%	2.818%**
	[1.255]	[1.037]	[2.232]
AR(2)	-0.037%	-0.280%	-0.740%
	[-0.074]	[0.413]	[-0.885]
AR(3)	0.279%	0.001%	0.248%
	[0.596]	[0.002]	[0.317]
CAR(1,3)	1.077%	0.631%	2.325%
	[1.232]	[0.568]	[1.541]
CAR(1,20)	-1.998%	-0.732%	1.512%
	[-1.167]	[-0.322]	[0.534]
CAR(4,20)	-3.075%**	-1.363%	-0.813%
	[-2.079]	[-0.690]	[0.341]

does not have a clear explanation for this phenomenon. In Table 3 it can be seen that winners do not experience a price reversal on the third day, while losers still experience a reversal for two of the three triggers. Hence, Table 4 shows that on the third trading day the effect again is larger for losers, since all values are positive. However, none of them is statistically significant. For the cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event, opposite results are found. The difference in average cumulative abnormal returns only has a positive sign at the 20% trigger for the period of 1 to 20 trading days after the event. The five other values are negative, which means that winners experience a greater price reversal during these two periods. This effect is mainly driven by the cumulative abnormal returns of 4 to 20 trading days after the event, which can be seen by the magnitudes for this event period. For the 10% trigger this effect even is statistically significant at the 5% level. This means that winners tend to experience the greatest part of the short-term price reversal effect a few days later than losers. Since Table 4 only shows clear results of losers to outperform winners in the first three trading days after the event, the third hypothesis, stating that the short-term price reversal after large one-day stock price movements is significantly larger for loser stocks than for winner stocks during the COVID-19 pandemic, can only be accepted for the cumulative abnormal returns of 1 to 3 trading days after the event. However, for the cumulative abnormal returns of 4 to 20 trading days after the event, winners tend to outperform losers.

5.2 Regression analysis

Table 5 presents the results of the regressions that are being used to test hypotheses 4 and 5. Besides, this table might provide additional evidence for hypotheses 6 to 9. Panel A shows the results for hypothesis 4, while Panel B shows the results for hypothesis 5. It can be seen that for both a total of nine different OLS regressions have been performed and year and industry fixed effects are included. Since Panel A only includes loser stocks and Panel B only winner stocks, D_{loser} is excluded. Since the Breusch-Pagan and White tests found heteroskedasticity for almost all regressions, all regressions are performed with robust standard errors to be consistent. Table 5 shows no evidence that larger initial stock price movements lead to bigger subsequent reversals, as none of the coefficients of the abnormal return on the event date is statistically significant. This result holds for both loser and winner stocks. The specific results for hypotheses 4 and 5 are discussed below.

Hypothesis 4

The fourth hypothesis states that the short-term price reversal effect after large one-day stock price decreases is significantly larger for value stocks than for growth stocks during the COVID-19 pandemic. Due to the price reversal, the cumulative abnormal returns are expected to be positive after large stock price decreases. This means that the variable D_{value} is expected to have a statistically significant positive coefficient. Panel A of Table 5 shows positive values for the -20% trigger, but for the -15% and -10% trigger this only holds for the cumulative abnormal return of 1 to 3 trading days after the event. Moreover, none of the positive coefficients is statistically significant, which means that the fourth hypothesis can be rejected. The results are consistent with the findings of Lakonishok, Shleifer and Vishny (1994), Haugen (1995) and Rozeff and Zaman (2002), for example, who all stated that regular investors undervalue value stocks. However, as this research assumes the stock market to be efficient (EMH), it was expected that this mispricing is corrected for. Since this is not the case, it can be concluded that the NYSE was not efficient during the COVID-19 pandemic and regular investors consistently undervalued value stocks. A possible

Table 5: Regression results of value versus growth stocks after large stock price movements

Notes: This table presents the regression results for different cumulative abnormal returns and triggers for loser stocks (Panel A) and winner stocks (Panel B) separately. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The abnormal return and bid-ask spread are determined on the event date. For the variables market capitalization (measured in USD millions) and trading volume (measured in millions of stocks) the natural logarithm is used to restrict the impact of outliers. While trading volume is determined for the event date, is the market capitalization obtained 5 trading days before the event. The investor sentiment is based on the Sentiment Index of Baker and Wurgler (2007). The CBOE volatility index represents the 30-day expected level of uncertainty in the stock market. The systematic and unsystematic risk are based on the pre-event estimation period and are estimated with the CAPM. As heteroskedasticity is found in almost all regression, all regression models use White-corrected standard errors to be consistent. These are reported in parentheses. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

Panel A. Loser stocks									
		-20%			**-15%**			**-10%**	
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	-0.052	-0.031	0.021	-0.091	0.128	0.218	0.019	0.316	0.297
	(0.173)	(0.303)	(0.251)	(0.124)	(0.256)	(0.234)	(0.115)	(0.201)	(0.177)
D_{value}	0.017	0.043	0.026	0.019	-0.028	-0.047	0.015	-0.015	-0.030
	(0.036)	(0.080)	(0.075)	(0.022)	(0.048)	(0.048)	(0.021)	(0.034)	(0.031)
BA_i	1.447	-0.744	-2.191	3.200***	2.716*	-0.484	1.663**	3.250***	1.588
	(1.233)	(1,945)	(1.738)	(0.877)	(1.559)	(1.493)	(0.699)	(1.175)	(1.171)
MC_i	0.009	0.006	-0.003	-0.004	-0.033*	-0.029*	-0.005	-0.021	-0.016
	(0.011)	(0.023)	(0.020)	(0.008)	(0.019)	(0.017)	(0.007)	(0.013)	(0.012)
TV_i	-0.001	-0.012	-0.011	0.007	0.015	0.008	0.006	0.017	0.012
	(0.008)	(0.019)	(0.016)	(0.008)	(0.019)	(0.016)	(0.006)	(0.012)	(0.011)
IS_i	0.009	-0.005	-0.014	0.002	0.044	0.042	-0.001	0.011	0.012
	(0.057)	(0.124)	(0.101)	(0.029)	(0.076)	(0.072)	(0.027)	(0.053)	(0.046)
VI_i	0.003	0.010***	0.007**	0.004**	0.010***	0.006**	0.003**	0.009***	0.006**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
SR_i	0.046***	0.053	0.007	0.041***	0.030	0.011	0.023**	0.028	0.005
	(0.016)	(0.039)	(0.035)	(0.010)	(0.028)	(0.025)	(0.009)	(0.022)	(0.020)
UR_i	-0.530*	-0.986	-0.456	-0.458*	-0.525	-0.067	-0.326	-1.070	-0.743
	(0.314)	(0.832)	(0.717)	(0.258)	(0.713)	(0.600)	(0.209)	(0.775)	(0.742)
Constant	-0.137	-0.215	-0.078	-0.185**	-0.073	0.112	-0.047	-0.098	-0.051
	(0.119)	(0.194)	(0.181)	(0.090)	(0.163)	(0.157)	(0.076)	(0.124)	(0.116)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193	193	193	317	317	317	452	452	452
R^2	0.345	0.299	0.234	0.345	0.288	0.201	0.201	0.252	0.209
Adjusted R^2	0.095	0.032	-0.059	0.192	0.121	0.014	0.069	0.128	0.078

Panel B. Winner stocks									
		10%			**15%**			**20%**	
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	-0.010	0.115	0.125	-0.047	0.049	0.096	-0.086	-0.120	-0.034
	(0.073)	(0.158)	(0.133)	(0.079)	(0.161)	(0.135)	(0.065)	(0.134)	(0.121)
D_{value}	0.019	-0.058**	-0.071***	0.015	-0.045	-0.049*	0.028	-0.010	-0.030
	(0.015)	(0.029)	(0.025)	(0.018)	(0.033)	(0.028)	(0.022)	(-0.037)	(0.035)
BA_i	-0.128	-0.477	-0.349	-0.402	-2.353*	-1.962**	-0.307	-1.204	-0.897
	(0.658)	(1.677)	(1.192)	(0.733)	(1.299)	(0.962)	(0.841)	(1.834)	(1.389)
MC_i	-0.006	-0.042***	-0.036***	-0.011	-0.056***	-0.045***	-0.007	-0.044***	-0.037***
	(0.006)	(0.011)	(0.010)	(0.007)	(0.013)	(0.012)	(0.008)	(0.013)	(0.011)
TV_i	0.006	0.011	0.006	0.005	0.014	0.008	0.007	0.017	0.010
	(0.005)	(0.010)	(0.009)	(0.006)	(0.012)	(0.010)	(0.005)	(0.011)	(0.009)
IS_i	0.0264	-0.0492	-0.076**	0.0143	-0.062	-0.076*	-0.00224	-0.054	-0.051
	(0.023)	(0.045)	(0.037)	(0.026)	(0.051)	(0.043)	(0.031)	(0.066)	(0.054)
VI_i	0.000	-0.002	-0.002	0.000	-0.001	-0.001	0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SR_i	0.011	0.033	0.022	0.012	0.054*	0.050**	0.019*	0.072***	0.059***
	(0.012)	(0.027)	(0.023)	(0.012)	(0.030)	(0.023)	(0.011)	(0.028)	(0.021)
UR_i	0.161	-1.414	-1.878**	-0.143	1.916**	-1.773**	-0.278	-2.294**	-2.016***
	(0.463)	(1.087)	(0.823)	(0.458)	(0.933)	(0.755)	(0.520)	(0.948)	(0.737)
Constant	-0.057	0.334**	0.391***	-0.295	0.352**	0.381***	-0.099	0.111	0.210
	(0.073)	(0.141)	(0.115)	(0.115)	(0.173)	(0.134)	(0.104)	(0.155)	(0.120)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	413	413	413	383	383	383
R^2	0.108	0.150	0.166	0.144	0.238	0.248	0.149	0.217	0.244
Adjusted R^2	-0.022	0.026	0.045	-0.017	0.095	0.106	-0.022	0.060	0.092

explanation for the fact there is not corrected for this mispricing could be that regular investors may have a systematic tendency to undervalue the ability of struggling business to recover (Haugen, 1995).

Hypothesis 5

The fifth hypothesis tests whether the short-term price reversal effect after large one-day stock price increases is significantly larger for growth stocks than for value stocks during the COVID-19 pandemic. As a price reversal effect is expected after large stock price increases, the cumulative abnormal returns are expected to be negative. Hence, the variable D_{value} is expected to have a statistically significant positive coefficient. However, Panel B of Table 5 shows that most of the coefficients are negative and some of them are even statistically significant. D_{value} only shows positive coefficients for the cumulative abnormal return of 1 to 3 trading days after the event, but non of these coefficients is significantly greater than zero. This means that the fifth hypothesis can be rejected. Again, the results are consistent with the findings of Lakonishok, Shleifer and Vishny (1994), Haugen (1995) and Rozeff and Zaman (2002), who all concluded that regular investors have a tendency to overvalue growth stocks. However, as this study assumes the stock market to be efficient (EMH), it was assumed that this mispricing is corrected for. It can be concluded that the NYSE was not efficient during the COVID-19 pandemic and regular investors consistently overvalued growth stocks. The opposite results might be caused by the fact that regular investors may have a systematic tendency to project growth too far into the future (Haugen, 1995).

Table 6 presents the results of the regression models that have been used to test hypotheses 6 to 9. The dummy variable D_{loser} is now included, since these regression models are conducted for both losers and winners. It can be seen that two different regression models have been conducted to answer these hypotheses, one with and one without the interaction term of D_{loser} and D_{value}, and that all regressions include year and industry fixed effects. All regressions are performed with robust standard errors, because the Breusch-Pagan and White tests showed heteroskedasticity to be present in almost all regressions. The specific results for hypotheses 6 to 9 are specified below.

Hypothesis 6

The sixth hypothesis states that the short-term price reversal effect after large one-day stock price movements is significantly impacted by transaction costs during the COVID-19 pandemic. The bid-ask spread proxies for transaction costs in this research. Table 6 shows that the coefficient of the bid-ask spread is positive for all 6 regressions and that the effect is the greatest for the cumulative abnormal returns of 1 to 20 trading days after the event. Since all coefficients have a positive sign, it means that wider bid-ask spreads lead to higher cumulative abnormal returns. Consequently, this means that wider bid-ask spreads enhance the short-term price reversal for loser stocks. This is confirmed by Panel A of Table 5, which shows that the bid-ask spread has a significantly positive effect on the cumulative abnormal returns of 1 to 3 and 1 to 20 trading days after the event for the -15% and -10% trigger. However, the result does not hold for the -20% trigger. Panel B of Table 5 shows that wider bid-ask spreads result in smaller cumulative abnormal returns for winner stocks, since all coefficients are negative. For the 15% trigger this effect even is statistically significant. This means that also for winners wider bid-ask spreads lead to bigger reversals. The results are in line with existing literature (Conrad & Kaul, 1993; Cox & Peterson, 1994; Conrad, Gultekin & Kaul 1997; Akhigbe, Gosnell & Harikumar 1998), who all found the bid-ask spread to significantly impact the price reversal effect. Since the results show that the bid-ask bounce significantly impacts the short-term price reversal effect for both loser and winner stocks, the sixth hypothesis can be accepted.

Hypothesis 7

The seventh hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by firm size during the COVID-19 pandemic. The market capitalization five trading days before the event date proxies for firm size in this paper. Table 6 shows that market capitalization has a negative coefficient for all six regressions. It can be seen that the effect is the greatest for the cumulative abnormal return of 1 to 20 trading days after the event and is statistically significant at the 1% level for this cumulative abnormal return and the one of 4 to 20 trading days after the event. As all coefficients are negative, this means that smaller firms experience larger cumulative abnormal returns. However, Panel A and B of Table 5 show different results and no negatively significant relationship between firm size and the short-term price reversal has been found for losers and winners. Winner stocks show negatively statistically significant coefficients, but this suggests a positive relationship with the short-term price reversal, since winner stocks experience short-term reversals when their cumulative abnormal returns are negative. The results are inconsistent with Zarowin (1990), Chopra, Lakonishok and Ritter (1992) and Ma, Tang and Hasan (2005), who all found that firm size reduces the cumulative abnormal return. This negative relationship might be explained by the fact that smaller firms have wider spreads and are less liquid than larger firms (Cox & Peterson, 1994). The last two also found proof for the size effect, but after removing the bid-ask bounce this effect disappeared. An additional regression model, which can be found in the Appendix, that uses the same methodology as Cox and Peterson (1994) has been conducted to examine whether the size effects indeed become smaller after removing the bid-ask bounce. In this model, the cumulative abnormal returns are calculated based on daily closing transaction prices and bid-ask averages, which are used to eliminate the bid-ask bounce. The results show that for both losers and winners the size effect indeed becomes smaller after removing the bid-ask bounce, since most of the coefficients have smaller coefficients after removing the bid-ask bounce. Hence, these results are consistent with the finding of Cox and Peterson (1994) that much of the reversal is attributable to the bid-ask bounce. Since, the results do not provide evidence for the size effect the seventh hypothesis can be rejected. Meaning that firm size does not significantly impacts the short-term price reversal after large one-day stock price changes.

Hypothesis 8

The eighth hypothesis states that the short-term price reversal effect after large one-day stock price movements is significantly impacted by liquidity during the COVID-19 pandemic. In this paper, the trading volume on the event date functions as a proxy for liquidity. Table 6 shows that the trading volume has a positive coefficient for all six regressions. The effect is the greatest for the cumulative abnormal returns of 1 to 20 trading days after the event and is statistically significant at the 5% in both models. For the cumulative abnormal return of 1 to 3 trading days after the event, the effect is statistically significant at the 10% level. Since all coefficients are positive, it means that the more liquid a stock is, the higher the cumulative abnormal returns after large stock price movements are. Consequently, this means that for loser stocks with high liquidity the short-term price reversal effect is larger than for loser stocks with less liquidity. This finding is confirmed by Panel A of Table 5, which shows positive coefficients for the -15% and -10% triggers. Panel B of Table 5 shows positive liquidity coefficients for winners in all regressions. This means that less liquid stocks have larger reversals, as winners experience reversals when they have negative cumulative abnormal returns. However, none of them is statistically significant. The positive relationship that has been found for loser stocks is not in line with existing literature (Bremer & Sweeney, 1991; Cox & Peterson, 1994; Lasfer, Melnik & Thomas, 2003; Butt, Högholm & Sadaqat, 2021), who all found the price reversal to be stronger in less liquid markets. Since no negatively significant relationship between liquidity and the short-term price reversal has been found for losers and winners, the eighth hypothesis is rejected.

Table 6: Regression results explaining the cumulative abnormal return after large stock price movements – Models 1 and 2

Notes: This table presents the regression results of Model 1 and 2 for different cumulative abnormal returns and triggers for a sample that consists of both losers and winners. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The abnormal return and bid-ask spread are determined on the event date. For the variables market capitalization (measured in USD millions) and trading volume (measured in millions of stocks) the natural logarithm is used to restrict the impact of outliers. While trading volume is determined for the event date, is the market capitalization obtained 5 trading days before the event. The investor sentiment is based on the Sentiment Index of Baker and Wurgler (2007). The CBOE volatility index represents the 30-day expected level of uncertainty in the stock market. The systematic and unsystematic risk are based on the pre-event estimation period and are estimated with the CAPM. As heteroskedasticity is found in almost all regression, all regression models use White-corrected standard errors to be consistent. These are reported in parentheses. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

		(1)			**(2)**	
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	-0.029	0.015	0.043	-0.029	0.016	0.044
	(0.062)	(0.108)	(0.091)	(0.062)	(0.108)	(0.091)
D_{loser}	0.010	0.040	0.030	0.011	0.030	0.019
	(0.024)	(0.043)	(0.037)	(0.026)	(0.047)	(0.040)
D_{value}	0.015	-0.025	-0.040**	0.016	-0.0322	-0.048**
	(0.012)	(0.022)	(0.019)	(0.014)	(0.027)	(0.023)
D_{loser} * D_{value}				-0.001	0.016	0.018
				(0.018)	(0.035)	(0.031)
BA_i	0.826	1.395	0.569	0.826	1.392	0.566
	(0.566)	(1.174)	(0.816)	(0.566)	(1.173)	(0.816)
MC_i	-0.007*	-0.031***	-0.025***	-0.007*	-0.031***	-0.025***
	(0.004)	(0.008)	(0.007)	(0.004)	(0.008)	(0.007)
TV_i	0.005*	0.014**	0.010	0.005*	0.015**	0.010
	(0.003)	(0.007)	(0.006)	(0.003)	(0.007)	(0.006)
IS_i	0.009	-0.019	-0.027	0.009	-0.020	-0.028
	(0.017)	(0.033)	(0.028)	(0.017)	(0.033)	(0.028)
VI_i	0.002*	0.005***	0.003**	0.002*	0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SR_i	0.021***	0.034**	0.013	0.021***	0.034**	0.013
	(0.007)	(0.017)	(0.015)	(0.007)	(0.017)	(0.015)
UR_i	-0.342**	-1.480**	-1.151*	-0.342**	-1.486**	-1.158*
	(0.172)	(0.638)	(0.642)	(0.173)	(0.639)	(0.643)
Constant	-0.039	0.094	0.132	-0.039	0.097	0.136
	(0.053)	(0.098)	(0.080)	(0.053)	(0.099)	(0.080)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	966	966	966	966	966
R^2	0.088	0.115	0.112	0.088	0.115	0.112
Adjusted R^2	0.018	0.048	0.044	0.017	0.047	0.044

Hypothesis 9

The ninth hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by investor sentiment during the COVID-19 pandemic. This study uses the Sentiment Index of Baker and Wurgler (2007) as a proxy for investor sentiment. Table 6 shows that investor sentiment has a positive effect on the cumulative abnormal return of 1 to 3 trading days after the event period. However, in both models, the two other cumulative abnormal returns have a negative coefficient. This negative relationship means that for low investor sentiment periods the cumulative abnormal return is larger. This is in line with Piccoli and Chaudhury (2018), who concluded that individuals tend to overreact economically and statistically significantly more during low investor sentiment periods rather than high sentiment periods. Hence, they stated that price reversals tend to be larger in times of low investor sentiment. However, Table 6 does not show any negatively statistically significant results. Panel A of Table 5 confirms this by also finding no negatively significant relationship between investor sentiment and the short-term price reversal. Panel B of Table 5 does find negative coefficients, which are statistically significant. However, since winner stocks experience short-term reversals if their cumulative abnormal returns are negative, the coefficients should have been positively significant to find evidence for this hypothesis. Since supporting evidence is not found, the ninth hypothesis is rejected.

Table 7 presents the results of the five different regression models (Model 3 to 7) that have been used to test hypotheses 10 and 11, which test whether (un)systematic risk has a significant impact on the short-term price reversal effect. Since systematic and unsystematic risk are highly correlated, the effect of both variables is firstly examined separately. However, Model 7 includes both variables. Several interaction terms have been included to further examine the effect of (un)systematic risk. Again, all models include year and industry fixed effects. Since the Breusch-Pagan and White tests showed heteroskedasticity to be present in almost all regressions, all the regressions are performed with robust standard errors. Furthermore, the results of Model 3 to 7 may provide additional evidence for hypotheses 6 to 9. The specific results for hypotheses 10 and 11 are specified below.

Hypothesis 10

The tenth hypothesis states that the short-term price reversal effect after large one-day stock price movements is significantly impacted by systematic risk during the COVID-19 pandemic. This paper uses the average CAPM beta of the pre- and post-event estimation periods as a proxy for systematic risk. The pre-event estimation period ranges from 105 to 6 trading days prior to the event, while the post-event estimation period ranges from 21 to 120 trading days after the event. At this way, there is controlled for a change in systematic risk, which might explain the short-term price reversal effect. The descriptive statistics in Section 3.2 show that the average pre-event beta of losers (1.384) is slightly larger than the mean of winners (1.324), which is consistent with Vermaelen and Verstringe (1986) and Ball and Kothari (1989). They found that a decrease (increase) in stock prices leads to an increase (decrease) in debt-equity ratios and consequently an increase in risk as measured by CAPM betas. In other words, they stated that during the test period losers are riskier than winners and hence losers are rewarded with higher expected returns. Furthermore, the descriptive statistics in Section 3.2 show a substantial increase in systematic risk for the post-event estimation period, which is consistent with Chan (1988), who concluded that risk is not constant over time.

Table 7 shows that the coefficients for systematic risk are positive for all regressions. The effect is the largest for the cumulative abnormal return of 1 to 20 trading days in the most extensive regression model (Model 7), in which also is controlled for unsystematic risk. The effect even is statistically significant at the 5% level. This positive relationship means that firms with higher systematic risk experience higher cumulative abnormal returns. Consequently, this means that loser stocks with high systematic risk experience greater short-term price reversals than loser stocks with low systematic risk. Panel A of Table 5 confirms this result, as it also finds positively statistically significant systematic risk coefficients for loser stocks. Panel B of Table 5 also shows positively statistically significant systematic risk coefficients for winner stocks, meaning that winner stocks with high systematic risk experience smaller price reversals than winner stocks with low systematic risk. Hence, evidence for the risk-change effect is found, which corresponds with Vermaelen and Verstringe (1986) and Ball and Kothari (1989). Additionally, Table 7 shows that loser stocks with high systematic risk experience smaller cumulative abnormal returns than winner stocks with high systematic risk, as the coefficients of the interaction term D_{loser} * SR_i are negative. Furthermore, the table shows that value stocks with high systematic risk experience significantly smaller cumulative abnormal returns than growth stocks with high systematic risk. Since evidence for the risk-change effect is found, the tenth hypothesis can be accepted. Meaning that systematic risk significantly impacts the short-term price reversal after large stock price decreases.

Hypothesis 11

The eleventh hypothesis tests whether the short-term price reversal effect after large one-day stock price movements is significantly impacted by unsystematic risk during the COVID-19 pandemic. This study uses the average unsystematic risk of the pre- and post-event estimation periods, which are the same as for hypothesis 10. By doing so, there is controlled for a change in unsystematic risk, which might explain the short-term price reversal effect. Table 7 shows negative coefficient for unsystematic in most regressions. The effect is the largest at in Model 7, which is the most extensive one. However, the results in this model are not statistically significant, but in Model 5 it can be seen that the results are statistically significant at the 5% level for the cumulative abnormal return of 4 to 20 trading days after the event. The negative relationship between unsystematic risk and the cumulative abnormal returns, means that highly unsystematic risk stocks experience smaller cumulative abnormal returns. Consequently, this means that loser with higher unsystematic risk experience smaller short-term price reversals. This is confirmed by Panel A of Table 5, as the unsystematic risk coefficients are negatively statistically significant. Panel B of

Table 5 also shows negatively statistically significant coefficients for unsystematic risk. The negative coefficients for winners are even more statistically significant. For winners, this negative relationship means larger short-term price reversals. This is consistent with McLean (2010), who found that for the US stock market price reversal are prevalent only in high unsystematic risk stocks. Additionally, Table 7 shows no statistically results for the interaction terms of unsystematic risk with D_{loser} and D_{value}. Since a statistically significantly positive relationship between unsystematic risk and the short-term price reversal is only found for winner stocks, the eleventh hypothesis can only be accepted for winners.

Table 7: Regression results explaining the cumulative abnormal return after large stock price movements – Models 3 to 7

Notes: This table presents the regression results of Model 3 to 7 for different cumulative abnormal returns and triggers for a sample that consists of both losers and winners. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The abnormal return and bid-ask spread are determined on the event date. For the variables market capitalization (measured in USD millions) and trading volume (measured in millions of stocks) the natural logarithm is used to restrict the impact of outliers. While trading volume is determined for the event date, is the market capitalization obtained 5 trading days before the event. The investor sentiment is based on the Sentiment Index of Baker and Wurgler (2007). The CBOE volatility index represents the 30-day expected level of uncertainty in the stock market. The systematic and unsystematic risk are based on the pre-event estimation period and are estimated with the CAPM. As heteroskedasticity is found in almost all regression, all regression models use White-corrected standard errors to be consistent. These are reported in parentheses. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

Variable	(3) CAR(1,3)	(3) CAR(1,20)	(3) CAR(4,20)	(4) CAR(1,3)	(4) CAR(1,20)	(4) CAR(4,20)	(5) CAR(1,3)	(5) CAR(1,20)	(5) CAR(4,20)	(6) CAR(1,3)	(6) CAR(1,20)	(6) CAR(4,20)	(7) CAR(1,3)	(7) CAR(1,20)	(7) CAR(4,20)
AR_i	-0.026	0.029	0.055	-0.026	0.029	0.055	-0.042	0.015	0.058	-0.042	0.014	0.056	-0.040	0.020	0.060
	(0.062)	(0.108)	(0.091)	(0.062)	(0.107)	(0.090)	(0.062)	(0.112)	(0.094)	(0.062)	(0.112)	(0.094)	(0.063)	(0.111)	(0.094)
D_{loser}	0.014	0.037	0.023	0.013	0.036	0.023	0.027	0.026	-0.001	0.027	0.023	-0.004	0.025	0.031	0.006
	(0.035)	(0.061)	(0.050)	(0.035)	(0.060)	(0.050)	(0.030)	(0.058)	(0.050)	(0.030)	(0.058)	(0.049)	(0.036)	(0.062)	(0.051)
D_{value}	0.016	-0.049*	-0.048**	0.063**	0.050	-0.013	0.014	-0.050*	-0.048**	0.012	-0.012	-0.024	0.045	0.039	-0.006
	(0.14)	(0.026)	(0.023)	(0.026)	(0.051)	(0.043)	(0.014)	(0.027)	(0.023)	(0.029)	(0.054)	(0.046)	(0.031)	(0.060)	(0.050)
D_{loser} * D_{value}	-0.002	0.011	0.014	-0.001	0.014	0.015	0.003	0.017	0.014	0.003	0.018	0.015	0.003	0.017	0.015
	(0.018)	(0.035)	(0.031)	(0.018)	(0.035)	(0.031)	(0.019)	(0.035)	(0.031)	(0.019)	(0.036)	(0.031)	(0.019)	(0.035)	(0.031)
BA_i	0.787	1.220	0.433	0.738	1.134	0.396	0.650	1.180	0.530	0.650	1.176	0.526	0.734	1.318	0.584
	(0.568)	(1.171)	(0.810)	(0.569)	(1.174)	(0.815)	(0.567)	(1.171)	(0.810)	(0.568)	(1.170)	(0.810)	(0.571)	(1.188)	(0.831)
MC_i	-0.004	-0.025***	-0.020***	-0.004	-0.023***	-0.020***	-0.005	-0.031***	-0.026***	-0.006*	-0.031***	-0.026***	-0.00456	-0.030***	-0.025***
	(0.004)	(0.007)	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)	(0.008)	(0.007)	(0.004)	(0.008)	(0.007)	(0.004)	(0.008)	(0.007)
TV_i	0.004	0.013**	0.009	0.004	0.013**	0.009	0.006*	0.017**	0.011*	0.006*	0.017**	0.011*	0.004	0.015**	0.01*
	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)	(0.006)
IS_i	0.012	-0.004	-0.016	0.009	-0.009	-0.018	0.010	-0.018	-0.028	0.010	-0.016	-0.026	0.004	-0.026	-0.029
	(0.017)	(0.033)	(0.028)	(0.017)	(0.033)	(0.028)	(0.017)	(0.033)	(0.028)	(0.017)	(0.032)	(0.027)	(0.017)	(0.033)	(0.028)
VI_i	0.002*	0.005***	0.003**	0.002*	0.005***	0.003**	0.002**	0.005***	0.003**	0.002**	0.005***	0.003**	0.002**	0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SR_i	0.019*	0.019	0.000	0.040***	0.059**	0.016							0.044***	0.073**	0.030
	(0.010)	(0.022)	(0.018)	(0.013)	(0.029)	(0.024)							(0.015)	(0.032)	(0.026)
D_{loser} * SR_i	-0.002	-0.004	-0.002	-0.002	-0.004	-0.002							-0.005	-0.004	-0.008
	(0.013)	(0.028)	(0.023)	(0.013)	(0.028)	(0.023)							(0.013)	(0.032)	(0.027)
D_{value} * SR_i				-0.032**	-0.056*	-0.024							-0.039**	-0.057*	-0.019
				(0.015)	(0.031)	(0.025)							(0.016)	(0.034)	(0.028)
UR_i							0.175	-1.287	-1.480**	0.142	-0.941	-1.084	-0.347	-1.754	-1.407
							(0.400)	(0.969)	(0.741)	(0.633)	(1.238)	(0.919)	(0.641)	(1.259)	(0.984)
D_{loser} * UR_i							-0.483	0.082	0.566	-0.487	0.124	0.611	-0.566	0.116	0.682
							(0.461)	(1.093)	(0.928)	(0.465)	(1.105)	(0.941)	(0.465)	(1.221)	(1.055)
D_{value} * UR_i										0.044	-0.459	-0.502	0.518	0.238	-0.280
										(0.611)	(1.150)	(0.939)	(0.615)	(1.183)	(1.011)
Constant	-0.058	0.016	0.074	-0.096	-0.052	0.045	-0.046	0.109	0.155	-0.045	0.091	0.136	-0.076	0.038	0.114
	(0.054)	(0.098)	(0.079)	(0.054)	(0.103)	(0.085)	(0.055)	(0.102)	(0.081)	(0.059)	(0.108)	(0.085)	(0.057)	(0.110)	(0.090)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	966	966	966	966	966	966	966	966	966	966	966	966	966	966	966
R^2	0.085	0.099	0.099	0.090	0.103	0.100	0.081	0.110	0.112	0.081	0.110	0.112	0.096	0.119	0.114
Adjusted R^2	0.014	0.030	0.030	0.019	0.033	0.030	0.010	0.041	0.043	0.009	0.040	0.043	0.022	0.047	0.042

CHAPTER 6 Conclusion

6.1 Contributions and implications

This study examines the short-term price reversal effect after large one-day stock price movements for NYSE stocks during the COVID-19 pandemic and examines whether this reversal is explained by investor overreaction. This research does so by analysing the (cumulative) abnormal returns following the large one-day stock price changes. When calculating the (cumulative) abnormal returns, the normal returns are calculated by using a variation of the CAPM, which is based on Cox and Peterson (1994). The only difference is that they used the market model, while this study uses the CAPM to calculate the normal returns. This method contains one pre-event and one post-event estimation period. The pre-event alphas and betas are calculated over an estimation period of 105 to 6 trading days prior to the event date, while the post-event alphas and betas are calculated over an estimation period from 21 to 120 trading days after the event date. Subsequently, the average values of the pre- and post-event CAPM alpha and beta are used to calculate the normal returns. The average values are taken, since the results show that risk is not constant over time, which is consistent with Chan (1988). A firm's beta, which proxies for systematic risk, increases substantially after large one-day stock price movements. The abnormal returns are calculated for the first three trading days after the event and the cumulative abnormal returns are calculated for the event periods of 5 trading days prior to 20 after the event and 1 to 3, 1 to 20 and 4 to 20 trading days after the event. Stocks that experienced a one-day price decline of at least 10% are referred to as 'loser' stocks, while stocks that experienced a one-day price increase that exceeds the trigger of 10% are characterized as 'winner' stocks. Hence, one-day price declines or increases of at least 10% are characterized as events. As robustness checks this paper also examines the triggers -20% and -15% for loses and 15% and 20% for winners. Multiple hypotheses are tested in this paper to answer the following research question:

Could regular investors in the U.S. stock market have profited from the overreaction hypothesis during the COVID-19 pandemic, if transaction costs, firm size, liquidity, investor sentiment and risk have been accounted for?

Firstly, this paper examines whether large one-day stock price decreases and increases are followed by a significant short-term price reversal during the COVID-19 pandemic. Consistent with prior studies (e.g., Bremer & Sweeney, 1991; Cox & Peterson, 1994), significant reversals have been found for both losers and winners. The results show that the reversal is the largest on the first trading day after the event and that the reversal is also present on second and third trading day after the event. For the first trading day after the event, the reversal even is statistically significant for the -20% and -10% triggers. Consequently, statistically significant cumulative abnormal returns over 1 to 3 trading days after the event are found for the -20% and -10% trigger. The average cumulative abnormal returns of 1 to 20 trading days after the event also show a price reversal for all three negative triggers, but these are not statistically significant. Since the average cumulative abnormal returns of 4 to 20 trading days after the event are negative or close to zero, it can be concluded that the short-term price reversal after large stock price decreases is mainly driven by the abnormal returns on the first three trading days after the event. The abnormal returns for winners show no price reversal on the first trading day after the event. However, on the second trading day statistically significant price reversals are observed for all three positive triggers, of which the effect is the strongest for the 20% trigger and the weakest for the 10% trigger. This is consistent with the overreaction hypothesis, which states that a greater magnitude of the initial price change leads to a greater price reversal. It seems that winners experience a one-day delay in the short-term price reversal compared to loser stocks. On the third trading day, the abnormal returns for all three triggers again do not show a price reversal. Hence, the cumulative abnormal returns over 1 to 3 trading days after the event are not statistically significant for winners at all triggers. However, the cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event date are negative for all three triggers, suggesting a reversal. Moreover, the average cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event date are statistically significant for the 10% trigger. Given the small price reversal in the first three days after the event date, the short-term price reversal after large stock price increases is mainly driven by the cumulative abnormal return of 4 to 20 trading days after the event date.

Additionally, this research tests whether the short-term price reversal after large one-day stock price movements is significantly larger for loser stocks than for winner stocks during the COVID-19 pandemic, as prior studies found that loser stocks outperform winners (e.g., De Bondt & Thaler, 1987; Zarowin, 1990). Consistent with the results discussed above, the reversal is the strongest for losers on the first and third trading day after the event and strongest for winners on the second day after the event. This is consistent with the findings of Akhigbe, Gosnell and Harikumar (1998), who also found the short-term price reversal to be slightly delayed for winners. The effect on the first day is even statistically significant for the 20% trigger. Consequently, losers experience larger cumulative abnormal returns over 1 to 3 trading days after the event, but this effect is for none of the triggers statistically significant. For the cumulative abnormal returns of 1 to 20 and 4 to 20 trading days after the event, opposite results are found, meaning that winners experience larger reversals. This can be explained by the observed delayed reversal for winner stocks. For the cumulative abnormal returns of 4 to 20 trading days after the event for the 10% trigger, this effect is statistically significant. Thus, losers only outperform winners in the first three trading days after the event and winners outperform losers over the period of 4 to 20 trading days after the event.

Furthermore, this study examines the difference between value and growth stocks on the short-term price reversal. The results are consistent with the findings of Lakonishok, Shleifer and Vishny (1994), Haugen (1995) and Rozeff and Zaman (2002), who all stated that regular investors undervalue value stocks and overvalue growth stocks. A possible explanation for these results might be that investors have a systematic tendency to project growth too far into the future and to undervalue the ability of struggling business to recover (Haugen, 1995). However, as this research assumes the stock market to be efficient (EMH), it was expected that these mispricings are corrected for. Since this is not the case, it can be concluded that the NYSE was not efficient during the COVID-19 pandemic and regular investors consistently undervalued value stocks and overvalued growth stocks.

Lastly, this paper examines multiple other possible explanations for the short-term price reversal that have been argued by existing literature. This paper also test whether the bid-ask bounce (Cox & Peterson, 1994), the size effect (Zarowin, 1990), liquidity (Bremer & Sweeney, 1991), investor sentiment (Piccoli & Chaudhury, 2018) and the risk-change effect (Vermaelen & Verstringe, 1986; Chan, 1988; McLean, 2010) explain the short-term price reversal. The results of this paper show that for both loser and winner stocks the bid-ask bounce leads to larger price reversals, meaning that the bid-ask bounce partially explains the short-term price reversal. For both losers and winners no evidence is found for the size effect to be explanatory for the short-term price reversal. Moreover, after removing the bid-ask bounce the effect was even less prevalent. These results are consistent with Cox and Peterson (1994), who found that much of the reversal is attributable to the bid-ask bounce and that the size effect disappeared after removing the bid-ask bounce. Furthermore, for both losers and winners, no evidence is found that liquidity and investor sentiment partially explain the short-term price reversal effect. Besides, the results of this study provide evidence for the risk-change effect, as it has been found that systematic risk for both losers and winners significantly leads to higher cumulative abnormal returns. Consequently, this means that loser stocks with high systematic risk experience larger reversals, while winners experience smaller reversals. This is consistent with Vermaelen and Verstringe (1986), who stated that loser stocks become riskier after the large one-day decline due to an increase in debt-equity ratios and hence are rewarded with higher returns. Additionally, the results of this paper show that systematic risk is not constant over time, which is in line with Chan (1988). Lastly, unsystematic risk is found to lead to significant smaller reversals for loser stocks and greater reversals for winner stocks.

Since the bid-ask bounce and the risk-change effect also account for the short-term price reversal effect after large one-day stock price movements in the US stock market during the pandemic, the reversal cannot only be attributed to overreaction. The results demonstrate that regular investors could have profited by performing the contrarian investment strategy, which means buying losers and shorting winners. However, due to the existence of the bid-ask bounce and risk-change effect this strategy would not consistently lead to profits for regular investors. Therefor, the answer to the research question is that regular investors could not have profited in the U.S. stock market from the overreaction hypothesis during the COVID-19 pandemic, if transaction costs, firm size, liquidity, investor sentiment and risk have been accounted for. In this paper, it is assumed that regular investors do know how to short, although short sellers normally are more sophisticated investors with a good understanding of the market and a careful risk management.

The results of this paper have theoretical implications for the field of behavioral finance, stock markets and psychology and more notably for investor overreaction, which violates the Efficient Market Hypothesis (EMH). This theory states that a stock price reflects all available information and hence securities are traded at their fair value. Although the US stock market is considered to be a developed market, this research provides evidence for investor overreaction. The existence of short-term price reversals has the practical implication that regular investors should invest against the market trend. They should carefully choose their investments during volatile times like the COVID-19 pandemic, as stock markets might be overreacted. Furthermore, the results of this paper show that investors tend to undervalue value stocks and overvalue growth stocks, meaning that investors should pay extra attention to their investments. Policymakers and regulators must be aware of the overreaction's existence as a market anomaly that occurs during turbulent times. Since investor overreaction ultimately can lead to stock market crash, overreaction needs to be observed, managed and regulated. Finally, the findings of this paper also contribute to academics, practitioners and investors in understanding the determinants of the US stock market in volatile times, like the COVID-19 pandemic.

6.2 Limitations and future research recommendations

Despite its significant contributions to existing literature, this paper has a few limitations that need to be mentioned when assessing the results. Firstly, in almost all regression models, heteroskedasticity is found. Although the White-corrected standard errors have been used, this still poses a limitation in interpreting the results. Secondly, this paper only uses stock price returns based on daily closing transaction prices. As a robustness check, it would also have been interesting to see what kind of results were found when using returns based on bid-ask averages for example. Thirdly, this study only examines the overreaction effect during the COVID-19 pandemic and does not include a reference period before or after the pandemic. Hence, the effect of the pandemic on the US stock market cannot clearly be observed. Additionally, this paper does not contain the entire duration of the pandemic due to a lack of data of the Baker and Wurgler (2007) Sentiment Index, which means that this paper does not fully capture the overreaction effect during the pandemic. Fourthly, this study does not examine the specific news types causing the large one-day stock price movements. These large daily changes could occur due to firm-specific reasons, such as disappointing financials or management issues, or market wide reasons like the number of confirmed COVID-19 cases or the announcement of the implementation of a lockdown. Examining the news types that caused the large one-day stock price movements would have provided useful insights. Lastly, this research makes no distinction between institutional investors and regular investors. Therefor, certain conclusions cannot be made about this paper's results.

This paper paves the way for future research about investor overreaction and the short-term price reversal effect. For example, future research could compare the short-term overreaction effect with periods before and after the pandemic. This would provide better insights in the effect of the pandemic on the US stock market. Future research could also examine the news types that caused the large one-day stock price movements and whether these news types are firm-specific or market wide. This will provide practical insights in explaining the short-term price reversal effect. Besides, future research could also further examine why winner stocks have a delay in their short-term reversal compared to loser stocks. This effect could be due to investor herding, asymmetric information, risk aversion, trading strategies, differences in market liquidity or due to the fact that investors may take more time to process the positive information. This causes a slower adjustment of winners' stock prices. Since existing literature has no clear explanation for this effect, future studies are recommended to examine this phenomenon. Furthermore, it would be interesting if future research could differentiate the behavior of institutional investors and regular investors or local and foreign investors. The latter could be interesting as foreign investors might face some currency risks. Moreover, future research could examine the differences in the overreaction effect between different countries. When doing so, it might be important to also control for macro-economic variables, such as (real) inflation, unemployment rates, import/export or (real) GDP.

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APPENDIX

Table 8: The evolution of the (Cumulative) Abnormal Returns over time

Notes: CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period ranges from 105 to 6 trading days prior to the event, while the post-event estimation period ranges from 21 to 120 trading days after the event.

Panel A. Loser stocks										
Quarter	**N**	**% of Total**	**CAR(-5,20)**	**AR(0)**	**AR(1)**	**AR(2)**	**AR(3)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
2020Q1	15	3.32%	0.66%	-30.49%	2.76%	12.98%	1.09%	16.83%	22.31%	5.48%
2020Q2	53	11.73%	0.27%	-19.00%	2.16%	-0.71%	1.28%	2.73%	10.50%	7.76%
2020Q3	50	11.06%	-25.02%	-16.77%	-1.58%	-0.97%	-0.01%	-2.56%	-11.33%	-8.78%
2020Q4	47	10.40%	-4.45%	-17.38%	1.75%	-0.76%	-0.38%	0.61%	2.55%	1.94%
2021Q1	54	11.95%	-4.38%	-17.50%	0.85%	0.18%	-0.80%	0.22%	-1.74%	-1.96%
2021Q2	43	9.51%	-17.49%	-15.79%	-0.28%	1.59%	0.36%	1.67%	-1.35%	-3.02%
2021Q3	40	8.85%	-18.49%	-17.71%	0.90%	0.03%	-0.81%	0.12%	-5.02%	-5.14%
2021Q4	46	10.18%	-15.68%	-17.57%	-0.27%	0.50%	0.38%	0.61%	-2.89%	-3.50%
2022Q1	54	11.95%	-6.13%	-20.31%	0.43%	1.13%	0.62%	2.18%	2.60%	0.42%
2022Q2	50	11.06%	-23.02%	-20.81%	2.80%	0.54%	-0.11%	3.24%	-1.50%	-4.74%

Panel B. Winner stocks										
Quarter	**N**	**% of Total**	**CAR(-5,20)**	**AR(0)**	**AR(1)**	**AR(2)**	**AR(3)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
2020Q1	15	2.92%	24.67%	49.42%	15.20%	-6.01%	-5.95%	3.24%	-12.53%	-15.77%
2020Q2	56	10.89%	43.74%	32.41%	2.14%	-0.84%	1.20%	2.49%	5.29%	2.80%
2020Q3	58	11.28%	15.46%	20.81%	-1.56%	-0.04%	-0.21%	-1.81%	-5.69%	-3.88%
2020Q4	54	10.51%	29.01%	25.95%	-0.72%	-0.68%	-0.64%	-2.04%	-0.99%	1.05%
2021Q1	58	11.28%	29.12%	28.53%	-0.60%	-1.50%	0.41%	-1.69%	-6.14%	-4.45%
2021Q2	50	9.73%	17.57%	17.57%	-0.78%	0.30%	0.62%	0.15%	-0.90%	-1.05%
2021Q3	52	10.12%	20.69%	21.02%	-1.96%	0.58%	0.63%	-0.75%	1.74%	2.49%
2021Q4	58	11.28%	9.64%	18.82%	2.07%	-0.17%	-1.34%	0.56%	-7.20%	-7.76%
2022Q1	60	11.67%	28.14%	23.08%	-1.18%	-0.27%	1.32%	-0.13%	2.40%	2.54%
2022Q2	53	10.31%	10.85%	19.72%	-1.80%	-1.27%	1.01%	-2.06%	-4.81%	-2.75%

Table 9: Industry distribution

Notes: Industry classification is based on the two digit SIC codes.

	Panel A. Loser stocks		Panel B. Winner stocks	
Industry	**N**	**% of Total**	**N**	**% of Total**
Mining	55	12.17%	64	12.45%
Construction	10	2.21%	10	1.95%
Manufacturing	108	23.89%	112	21.79%
Transportation and public utilities	29	6.42%	53	10.31%
Wholesale trade	10	2.21%	17	3.31%
Retail trade	51	11.28%	48	9.34%
Finance, insurance and real estate	62	13.72%	75	14.59%
Services	127	28.10%	135	26.26%

Table 10: Additional regression results explaining the size effect

Notes: This table presents additional regression results explaining the size effect for different cumulative abnormal returns and triggers for loser stocks (Panel A) and winner stocks (Panel B) separately. CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. For the (C)AR variables, the normal returns are calculated by using the average of the pre- and post-event parameters of the CAPM. The pre-event estimation period is 105 to 6 days prior to the event, while the post-event estimation period is 21 to 120 days after the event date. The abnormal return is determined on the event date, while the market capitalization obtained 5 trading days before the event. For the variable market capitalization (measured in USD millions) the natural logarithm is used to restrict the impact of outliers. As heteroskedasticity is found in almost all regression, all regression models use White-corrected standard errors to be consistent and are reported in parentheses. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

Panel A. Returns based on transaction prices

Panel A.1 Loser stocks

	-20%			**-15%**			**-10%**		
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	-0.220	-0.436	-0.028	-0.246	-0.379	0.027	-0.154	-0.206	0.056
	(0.226)	(0.326)	(0.243)	(0.159)	(0.248)	(0.183)	(0.136)	(0.219)	(0.156)
MC_i	0.001	-0.012	-0.012	-0.006	-0.021*	-0.014	-0.003	-0.009	-0.005
	(0.011)	(0.016)	(0.012)	(0.006)	(0.011)	(0.009)	(0.004)	(0.008)	(0.006)
Constant	-0.110	-0.226	-0.029	0.047	0.198	0.180	0.096	0.193	0.117
	(0.105)	(0.152)	(0.112)	(0.089)	(0.178)	(0.110)	(0.073)	(0.138)	(0.084)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193	193	193	317	317	317	452	452	452
R^2	0.210	0.211	0.197	0.186	0.176	0.132	0.116	0.129	0.132
Adjusted R^2	-0.031	-0.030	-0.049	0.035	0.024	-0.028	-0.004	0.011	0.013

Panel A.2 Winner stocks

	10%			**15%**			**20%**		
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	0.052	0.141	0.078	-0.008	0.095	0.096	0.011	0.083	0.046
	(0.068)	(0.135)	(0.114)	(0.075)	(0.150)	(0.125)	(0.066)	(0.132)	(0.113)
MC_i	-0.004	-0.026***	-0.021***	-0.008*	-0.034***	-0.024***	-0.004	-0.014	-0.009
	(0.004)	(0.007)	(0.006)	(0.005)	(0.009)	(0.008)	(0.006)	(0.011)	(0.009)
Constant	0.008	0.002	0.005	-0.001	0.035	0.026	-0.033	-0.224	-0.194
	(0.036)	(0.135)	(0.130)	(0.057)	(0.166)	(0.159)	(0.070)	(0.165)	(0.172)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	413	413	413	383	383	383
R^2	0.096	0.126	0.129	0.138	0.176	0.181	0.137	0.157	0.191
Adjusted R^2	-0.011	0.022	0.026	0.005	0.048	0.055	-0.013	0.011	0.051

Panel B. Returns based on averages of bid and ask prices									
Panel B.1 Loser stocks									
	-20%			**-15%**			**-10%**		
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	-0.216	-0.430	-0.029	-0.256	-0.351	0.028	-0.114	-0.282	0.058
	(0.218)	(0.319)	(0.264)	(0.201)	(0.218)	(0.180)	(0.107)	(0.239)	(0.172)
MC_i	0.001	-0.011	-0.010	-0.006	-0.012	-0.014	-0.004	-0.007	-0.005
	(0.011)	(0.015)	(0.012)	(0.006)	(0.008)	(0.009)	(0.005)	(0.008)	(0.007)
Constant	-0.118	-0.217	-0.026	0.047	0.187	0.188	0.134	0.155	0.117
	(0.111)	(0.146)	(0.108)	(0.089)	(0.166)	(0.119)	(0.102)	(0.121)	(0.084)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193	193	193	317	317	317	452	452	452
R^2	0.208	0.209	0.200	0.186	0.174	0.131	0.116	0.123	0.132
Adjusted R^2	-0.032	-0.030	-0.038	0.035	0.027	-0.026	-0.004	0.009	0.013

Panel B.2 Winner stocks									
	10%			**15%**			**20%**		
Variable	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**	**CAR(1,3)**	**CAR(1,20)**	**CAR(4,20)**
AR_i	0.051	0.121	0.077	-0.007	0.105	0.086	0.041	0.073	0.076
	(0.064)	(0.104)	(0.111)	(0.071)	(0.188)	(0.109)	(0.096)	(0.117)	(0.153)
MC_i	0.002	-0.009*	-0.012**	-0.001	-0.018**	-0.009*	0.004	-0.004	-0.002
	(0.004)	(0.005)	(0.005)	(0.001)	(0.006)	(0.005)	(0.002)	(0.002)	(0.001)
Constant	0.008	0.002	0.005	-0.001	0.035	0.026	-0.033	-0.224	-0.194
	(0.036)	(0.135)	(0.130)	(0.057)	(0.166)	(0.159)	(0.070)	(0.165)	(0.172)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	413	413	413	383	383	383
R^2	0.094	0.124	0.133	0.138	0.173	0.180	0.137	0.151	0.191
Adjusted R^2	-0.013	0.022	0.036	0.005	0.051	0.056	-0.013	0.010	0.051

Table 11: Pearson correlation table

Notes: CAR(-5.20) represents the cumulative abnormal return over 5 days prior to the event to 20 days after. AR(1) corresponds to the abnormal return of 1 day after the event. The other (C)AR variables are structured the same way. The statistical significance of the t-statistics is indicated by the asterisks behind the mean value, representing the 10% (*), 5% (**) and 1% (***) levels.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(1) Return at event date	1.000																								
(2) CAR(-5,20)	0.536*	1.000																							
(3) AR(0)	0.995*	0.543*	1.000																						
(4) AR(1)	-0.000	0.187*	-0.002	1.000																					
(5) AR(2)	-0.121*	0.075*	-0.117*	-0.164*	1.000																				
(6) AR(3)	0.008	0.150*	0.015	-0.024	-0.030	1.000																			
(7) CAR(1,3)	-0.066*	0.265*	-0.062*	0.649*	0.430*	0.497*	1.000																		
(8) CAR(1,20)	-0.035	0.627*	-0.028	0.341*	0.249*	0.262*	0.540*	1.000																	
(9) CAR(4,20)	0.003	0.575*	0.008	-0.044	0.029	0.026	-0.001	0.831*	1.000																
(10) Dummy loser	-0.880*	-0.448*	-0.882*	0.036	0.073*	-0.010	0.063*	0.039	0.007	1.000															
(11) Dummy value	0.062*	0.043	0.064*	0.020	0.040	0.033	0.055	-0.024	-0.069*	-0.039	1.000														
(12) Bid-ask spread	0.063*	0.047	0.069*	0.0305	0.015	0.013	0.038	0.025	-0.005	-0.037	0.205*	1.000													
(13) Market capitalization	-0.163*	-0.232*	-0.165*	-0.056	0.040	-0.052	-0.048	-0.096*	-0.075*	0.114*	-0.449*	-0.277*	1.000												
(14) Trading volume	0.057	0.029	0.056	0.020	-0.017	0.006	0.008	0.014	0.007	-0.029	-0.232*	-0.387*	0.527*	1.000											
(15) Investor sentiment	-0.063*	-0.092*	-0.062*	-0.023	0.038	-0.012	-0.002	-0.039	-0.038	-0.002	-0.164*	0.003	0.200*	0.024	1.000										
(16) CBOE Volatility Index	0.002	0.111*	0.025	0.099*	0.059	0.045	0.129	0.155*	0.082*	0.035	0.099*	0.099*	-0.144*	-0.025	-0.339*	1.000									
(17) Pre-event alpha	-0.137*	-0.258*	-0.153*	-0.073*	0.004	-0.066*	-0.088*	-0.236*	-0.219*	0.120*	-0.021	-0.098*	0.192*	0.104*	-0.018	-0.158*	1.000								
(18) Post-event alpha	0.013	-0.154*	0.003	-0.023	-0.077*	-0.011	-0.068*	-0.201*	-0.196*	-0.009	0.105*	0.011	-0.142*	0.014	-0.265*	0.069*	0.047	1.000							
(19) Average alpha	-0.101*	-0.276*	-0.118*	-0.065*	-0.058	-0.061*	-0.115*	-0.283*	-0.261*	0.082*	0.063*	-0.055	0.033	0.062*	-0.174*	-0.064*	0.657*	0.711*	1.000						
(20) Pre-event beta	0.003	-0.025	0.004	-0.019	0.015	0.048	0.020	0.027	0.022	-0.009	-0.011	-0.172*	0.021	0.199*	-0.005	-0.023	-0.042	0.141*	0.053	1.000					
(21) Post-event beta	-0.026	0.049	-0.024	0.085*	0.008	0.057	0.099*	0.050	-0.004	0.040	-0.008	-0.172*	0.033	0.237*	-0.032	0.149*	-0.008	0.079*	-0.073*	0.390*	1.000				
(22) Average beta	-0.015	0.025	-0.013	0.043	0.013	0.063*	0.073*	0.047	0.010	0.020	-0.011	-0.206*	0.033	0.262*	-0.023	0.081*	-0.029	0.031	0.016	0.816*	0.851*	1.000			
(23) Pre-event unsystematic risk	0.040	0.049	0.035	-0.004	-0.008	0.031	0.009	-0.011	-0.027	0.023	0.132*	0.017	-0.276*	0.053	-0.300*	0.163*	0.176*	0.127*	0.191*	0.306*	0.292*	0.358*	1.000		
(24) Post-event unsystematic risk	0.022	0.025	-0.021	0.025	-0.056	0.055	0.016	-0.060	-0.083*	0.067*	0.124*	0.050	-0.277*	-0.028	-0.134*	0.141*	-0.098*	0.373*	0.214*	0.075*	0.309*	0.237*	0.298*	1.000	
(25) Average unsystematic risk	-0.026	0.017	-0.028	0.003	-0.046	0.035	-0.006	-0.051	-0.063*	0.065*	0.148*	0.036	-0.292*	-0.019	-0.216*	0.146*	0.036	0.339*	0.407*	0.182*	0.301*	0.293*	0.700*	0.731*	1.000