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Emotion and Exaggeration: A Deep Dive into Investor Sentiment and Its Impact on Market Overreactions

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ABSTRACT

This study investigates stock market reactions, particularly the overreactions and subsequent price reversals following notable price declines of more than 10%. The research aims to understand the drivers behind price reversals and assess the presence of overreaction in the market. By accounting for variables like bid-ask price differences and the size of a company, it is found that overreactions are not a dominant factor. To further analyze investor behaviors in changing market conditions, an aligned sentiment index is developed and examined against price reversals. However, the findings indicate that sentiment does not significantly impact price reversals in either the short or medium term. This underscores the importance of considering a range of factors when analyzing stock market movements and challenges the notion of sentiment as a primary influencer.

Keywords: Stock Market Overreactions, Investor Sentiment, Market Anomalies, Aligned Sentiment, Behavioral Finance, Sentiment Indexes, Market Events.

JEL Classification: G02, G12, G14

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CHAPTER 1 Introduction

1.1. Drive behind Financial Studies

Previous research in experimental psychology has significantly enhanced our understanding of how individuals deviate from rational decision-making. These studies underscore the influence of factors like heuristics, cognitive biases, framing, and subjective perceptions on people's judgments and choices. In the financial markets field, psychological behavior has been extensively explored as researchers and economists aim to gain deeper insights into investor decision-making processes.

Recognizing the importance of comprehending psychological investor behavior is essential. It offers valuable insights into the drivers behind asset price movements and forms the foundation for predictive models for asset returns. These models seek to uncover patterns and anomalies in market dynamics, ultimately boosting the accuracy of asset price predictions. Precise predictive asset return models confer a competitive edge in financial markets, aligning with investors' objectives of devising profitable investment strategies to achieve personal financial gains.

1.2. Tendency to Overreact

One interesting psychological observation is the tendency of individuals to overreact to unexpected news due to various cognitive and emotional factors. Biases like the availability heuristic, where noticeable information has a bigger influence on judgments, together with loss aversion and confirmation bias, play a part in this overreaction. These psychological inclinations cause people to show exaggerated reactions and make irrational decisions when confronted with unexpected news. This phenomenon has also been observed in financial markets, where investors tend to overreact to unexpected positive or negative information, which is introduced in the literature as the concept of the overreaction effect.

1.3. Contribution and Relevance

This paper aims to delve into the overreaction effect in financial markets and shed light on its characteristics. The paper will specifically examine how the phenomenon of investor overreaction interacts with varying market dynamics and changing investor sentiment. By analyzing the relationship between the overreaction effect and investor sentiment, we can gain insights in the dynamics of market behavior on the psychological decision-making by individuals.

This research builds upon and expands the existing literature in the realm of stock market overreactions and the integral role investor sentiment plays in shaping financial behavior. While the pioneering work by de Bondt and Thaler sheds light on Stock Market Overreaction, this paper takes a step further by specifically examining stock price reversals subsequent to pronounced price drops, drawing inspiration from studies by Bremer and Sweeney, as well as Cox and Peterson. Moreover, while Piccoli and Chaudhury delved into the nexus between investor sentiment and the initial winner-loser effect highlighted by de Bondt and Thaler, our study carves a niche by emphasizing the behavioral nuances associated with overreaction, especially when confronted with investor losses as examined by Bremer and Sweeney. In doing so, this paper enriches the discourse on behavioral finance by offering a nuanced perspective on the interplay between sentiment and overreactions in the context of market downturns.

The primary research question this paper seeks to address is:
"Is there a demonstrable existence of market overreaction, particularly in the context of notable stock prices, and how does investor sentiment influence the overreaction effect?"

1.4. Design of the Study

The remainder of the paper is organized as follows: Chapter 2 presents a comprehensive literature review, detailing previous research on investor overreaction and sentiment analysis in the financial domain. Chapter 3 focuses on data discussion, providing an overview of the datasets employed and their significance in the context of the study. Chapter 4 outlines the research methodology, elucidating the analytical techniques and frameworks utilized. Chapter 5 presents the empirical results, highlighting the intricate dynamics between investor sentiment and overreaction. Chapter 6 wraps up the study with the conclusion and discussion, emphasizing the broader implications of the findings and potential avenues for future research.

CHAPTER 2 Literature Review

In this chapter, key topics in financial markets and investor behavior are presented. First, standard theories are discussed – efficient market hypothesis, market anomalies, and behavioral finance. Thereafter, we delve specifically into stock market overreaction, price reversals, and longer-term performance implications. Lastly, the paper discusses psychological investor sentiment, its role during periods of market distress, and the interaction with stock market overreaction.

2.1. Standard Theory

2.1.1. Traditional Rationality and Efficient Market Hypothesis

Historically, the foundation of financial studies rested on traditional rationality. This theory conceives individuals as consistently rational, optimizing decision-makers. Given full information access and an objective processing capability, their choices should reflect their genuine preferences and values (Fama, 1970).

Anchored in rationality theory, the Efficient Market Hypothesis (EMH) posits that financial markets are comprehensive reflectors of all extant information. Thus, stock prices should faithfully represent securities' true values, with any deviations swiftly corrected by astute investors. However, real-world evidence occasionally challenges this idealized market behavior.

2.2. Market Anomalies

Market anomalies challenge this theory of expected rationality (Fama, 1965). Market anomalies are patterns or inconsistencies in asset prices that cannot be explained by traditional rationality theories, posing a challenge to the assumptions of rationality and the efficient market hypothesis (Fama, 1970). These anomalies can be categorized into different groups, each highlighting distinct patterns and inconsistencies in asset prices.

2.2.1. Seasonal Anomalies

Seasonal anomalies are market-inefficient patterns observed at specific times of the year (Lakonishok and Smith, 1988). Notable examples include the January Effect, where stock prices experience an increase and outperform other months (Thaler, 1987b), and the Turn-of-the-Month Effect, where stock prices tend to have positive returns around the end of one month and the beginning of the next (Thaler, 1987a; Lakonishok and Smith, 1988).

2.2.2. Behavioral Anomalies

These anomalies underscore the impact of psychological biases on market outcomes. For instance, the overreaction effect (de Bondt and Thaler, 1985) exemplifies price deviations due to excessive investor reactions. Similarly, herding behavior sees investors echoing the decisions of their peers, sometimes at the cost of individual rationale (Bikhchandani and Sharna, 2000).

The anchoring bias, on the other hand, occurs when investors heavily rely on an initial reference point or information when making investment decisions (Tversky and Kahneman, 1974). This anchor influences their subsequent judgments and evaluations, leading to biases in perception and decision-making, potentially resulting in missed opportunities and the persistence of incorrect valuations (Furnham and Boo, 2011).

Overall, behavioral anomalies highlight human behavior in financial markets, suggesting that market inefficiencies and mispricing may occur due to psychological biases and cognitive limitations. Recognizing and analyzing these anomalies can provide insights into market trends, recurring patterns, and potential trading opportunities.

2.2.3. Value Anomalies

Value anomalies are observed when certain stocks with specific fundamental characteristics outperform stocks with opposite traits, such as differences in earnings' yields or market values (Reinganum, 1981). One well-known value anomaly is the Value-Growth effect, where value stocks, with relatively low price-to-book ratios, tend to outperform growth stocks, which have higher price-to-book ratios (Fama and French, 1998). A potential factor contributing to the value-growth effect is the tendency of value stocks to offer higher dividend yields, making them more attractive to investors seeking additional income (Miller and Modigliani, 1961). Traditional studies refer to this phenomenon as the Dividend Yield Effect. However, further research challenges the belief that dividend policy directly affects stock prices, suggesting that investors should focus more on fundamental factors like earnings and risk when valuing stocks (Black and Scholes, 1974).

2.2.4. Momentum Anomalies

Momentum anomalies occur when stocks that have performed well or poorly in the past tend to continue displaying similar performance in the future (Jegadeesh and Titman, 1993). This effect is most pronounced in the short-term performance of stocks (Conrad and Kaul, 1998). In contrast, the Reversal

Effect suggests that stocks that have performed well in the past subsequently experience a period of underperformance, while poorly performing stocks tend to show a subsequent period of outperformance (Conrad and Kaul, 1998). This effect is particularly prominent in the medium-term performance of stocks. However, when examining the longer term, extended research reveals the concept of mean reversion, where asset prices tend to return to their long-term average or equilibrium level, indicating that stock prices are ultimately reflective of their fundamental values (Poterba and Summers, 1998).

2.2.5. Size Anomalies

The presence of size anomalies reveals a consistent pattern where stocks of companies with smaller market capitalizations tend to outperform stocks of companies with larger market capitalizations (Banz, 1981). This phenomenon, known as the Size Effect, has demonstrated persistence across various markets and time periods, underscoring the robustness of this anomaly. The finding challenges the traditional view of efficient markets, which assumes that higher returns are only associated with higher levels of risk.

To conclude, exploring market anomalies offers a nuanced understanding of financial markets, underscoring their unpredictability and the behavioral factors influencing them. By unpacking these intricacies, both investors and researchers can refine their strategies and perspectives.

2.3. Behavioral Finance

Behavioral finance emerged as a response to traditional finance theories, which predominantly centered on rational investor behavior. By incorporating insights from psychology, behavioral finance offers a more realistic portrayal of financial decision-making, emphasizing that investors are not just influenced by data and analytics but also by emotions, cognitive biases, and social factors.

A notable example is the concept of overconfidence. Investors often overestimate their judgment accuracy and abilities (Statman et al., 2006). This tendency can lead to unwarranted risk-taking and potentially suboptimal investment decisions, causing speculative behavior and the tendency to overlook contrary evidence (Odean, 1999).

Another fundamental bias is loss aversion. Investors display a stronger inclination to avoid losses than to acquire equivalent gains. This emotional response to potential losses is so intense that the displeasure of a loss outweighs the satisfaction of an equivalent gain (Tversky and Kahneman, 1991).

As a result, investors may hold onto declining investments hoping for a future recovery, a phenomenon termed the 'disposition effect' (Shefrin and Statman, 1985).

Furthermore, a core component of behavioral finance is understanding investor sentiment. Investor sentiment encapsulates the collective mood or attitude of investors towards the market. It significantly shapes their buying and selling decisions, thus influencing market dynamics (Barberis et al., 1998). Exploring the relationship between sentiment indicators and market outputs like returns, volatility, and trading volume is pivotal. This aids in discerning whether investor sentiment can predict market movements, anomalies, or even provide insight into market bubbles and crashes.

Furthermore, behavioral finance acknowledges that individuals' risk preferences and decision-making processes are influenced by factors beyond purely economic considerations. Social and psychological factors potentially play a role in shaping investor behavior. Overall, the integration of psychological insights into finance offers a more comprehensive understanding of investor behavior, illustrating how individuals make decisions under risk and uncertainty while highlighting the psychological biases and cognitive limitations that can impact their choices.

2.4. Prospect Theory

A significant breakthrough in the study of decision-making under uncertainty is the Prospect Theory. Developed by Kahneman and Tversky in 1979, it postulates that individuals assess potential outcomes based on their subjective perception of gains and losses relative to a reference point.

The theory introduces the concept of the value function. This suggests that the perceived value of gains decreases as the amount rises, whereas the perceived pain from losses intensifies as they increase (Barberis et al., 2001). Furthermore, when evaluating potential outcomes, individuals often overweight small probabilities and underweight large probabilities—a phenomenon known as probability weighting.

Harnessing insights from both behavioral finance, with its understanding of biases like overconfidence and loss aversion, and Prospect Theory's innovative concepts can pave the way for more nuanced investment strategies. Recognizing and strategically navigating these biases and behavioral patterns can enable investors to spot and capitalize on market inefficiencies.

2.5. Relevance of Behavioral Insights

The exploration of investor behavior, especially through the lens of behavioral finance and its associated biases, is pivotal to our understanding of market dynamics. While traditional finance theories provide a foundation, they sometimes don't fully account for observed market anomalies and behaviors. Integrating a behavioral perspective enriches our comprehension, shedding light on psychological mechanisms influencing investment decisions and market reactions. One such behavior, which this study deeply probes into, is stock market overreactions—a phenomenon where the market's reaction to news events is more extreme than warranted. As we delve deeper, the interplay between overreactions and the broader theme of investor sentiment will be further elaborated upon.

2.6. Overreaction in the Stock Market

The interplay between behavioral finance and Prospect Theory, which bring psychological insights to financial decisions and elucidate decision-making under risk respectively, has enriched the understanding of market anomalies. One such striking anomaly is the tendency of individuals to overreact to unexpected news (Kahneman et al., 1982).

2.6.1. Stock Price Overreaction

This phenomenon was primarily introduced by de Bondt and Thaler (1985) as the overreaction effect where individuals overreact to sudden and unexpected news in financial markets. They demonstrated that stock prices tend to exhibit exaggerated reactions, causing them to move disproportionately in response to new information. The paper presents empirical evidence of subsequent reversals in the returns of stocks experiencing extreme price moments, with stocks that had previously performed poorly tending to outperform those that had performed well (referred to as the "winner-loser effect").

Building upon their earlier work, de Bondt and Thaler (1987) extended their analysis to explore the impact of seasonal patterns on overreactions and examining factors like size, seasonality, and time-varying risk premia. Despite controlling for these factors, the winner-loser effect persisted, indicating that it was not solely driven by size or the observed seasonal patterns.

2.6.2. Subsequent Price Reversals

Drawing upon de Bondt and Thaler's groundwork, Bremer and Sweeney (1991) delved into the dynamics of stocks that witnessed substantial price declines. While the phenomena of reversals in stock returns after significant declines was initially noted by Brown et al. (1988) and Atkins and Dyl

(1990), Bremer and Sweeney specifically examined substantial price declines. Their research confirmed that stocks undergoing large price drops tended to exhibit subsequent positive returns, especially in the immediate three trading days that followed. A deeper insight from their study revealed that the magnitude of the stock price drop and its subsequent reversal was positively correlated, and that stocks with a higher trading volume experienced a more pronounced reversal effect, underlining the role of liquidity in the phenomenon.

Building on this, Cox and Peterson (1994) provided a more nuanced perspective, differentiating between short-term reversals and the longer-term stock performance after significant one-day declines. They identified that as market liquidity improved over time due to a myriad of factors such as increased investor participation, advancements in trading technology, and heightened investor education, the magnitude of reversals diminished.

Cox and Peterson emphasized the significance of the bid-ask spread in understanding reversal patterns. They indicated that market illiquidity might explain some of the observations made by earlier researchers. By examining the difference between closing transaction prices and the average bid and ask prices, they highlighted the potential role of bid-ask spreads in such reversals. Particularly for smaller stocks, where bid-ask spreads are typically more substantial, they identified a phenomenon known as the 'bid-ask bounce' as a pivotal contributor to price reversals. As a result, both market liquidity and the size of the bid-ask spreads are essential considerations when analyzing stock price reversals.

Further extending their insights, Cox and Peterson observed that after a four-day period subsequent to the price decline, securities tend to enter a prolonged phase of relatively poor performance, wherein the post-drop recovery (the reversal) itself is reversed. This underlined a notable long-term consequence resulting from the initial decline.

Understanding stock market overreactions is crucial for this paper. The prior literature provides a foundation, but this study seeks to delve deeper, especially into the interplay between overreactions and investor sentiment. The next sections will discuss how sentiment might amplify or mitigate overreactions and the implications for market efficiency and investor strategies.

2.7. Investor Sentiment in the Stock Market

Previous studies have highlighted the importance of considering factors beyond stock market overreaction when examining stock price dynamics. One influential factor that impacts stock market movements and investor behavior, as discussed earlier in behavioral finance studies, is investor sentiment. It captures the general mood of investors, oscillating between optimism and pessimism, and has a profound impact on shaping market trends. High levels of investor sentiment may lead to overreaction in stock prices as investors take on greater risk due to excessive optimism. Conversely, low levels of investor sentiment may result in market underreaction as investors become risk averse. Understanding the impact of investor sentiment underscores the role in periods of extreme market volatility, such as bubbles and crashes, which are difficult to rationalize by solely traditional market fundamentals..

Barberis, Shleifer, and Vishny (1998) delved deep into behavioral facets affecting stock prices. They proposed a unique model focusing on the attention investors pay to the strength and weight of evidence, emphasizing that stock prices might underreact to statistically significant but less forceful corporate announcements. On the contrary, stocks might overreact to consistent patterns of news. This nuanced analysis sheds light on the intricacies of investor behavior in response to different types of news. However, while Barberis et al. offer valuable theoretical insights, they call for more empirical work to solidify their findings.

The paper by Fisher and Statman (2000) explores the interplay between investor sentiment and stock returns. Their findings suggest a significant contrary relationship between investor sentiment and future S&P 500 returns. This evidence posits investor sentiment as a pivotal metric in identifying potential investment opportunities, especially in times of market uncertainty. Essentially, a contrarian approach, where investors act against prevailing market sentiment, can be a profitable strategy.

Over time, various models have been created to understand how investor sentiment forms and affects markets. However, in empirical terms, investor sentiment remains unobservable and requires estimation. Baker and Wurgler (2006) made significant strides by introducing the Investor Sentiment Index. This index combines six investor sentiment proxies, including the closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, equity share in new issues, and the dividend premium. Each proxy is based on different aspects of investor behavior and market conditions.

While the paper by Baker and Wurgler (2006) introduces the Sentiment Index, it does not directly present empirical findings or implications regarding the index's performance in predicting stock returns or market behavior. However, the Sentiment Index still became a widely used and one of the most important metric in studies on investor sentiment, indicating its significance in understanding market dynamics and investor behavior. Researchers frequently rely on the Sentiment Index as a valuable tool to investigate the role of sentiment in financial markets. Later on, in a subsequent paper by Baker and Wurgler (2007), the authors use the Sentiment Index to empirically examine its impact on stock prices, trading volume, and market behavior. The study identifies waves of sentiment that affect stocks, particularly those that are difficult to value and costly to arbitrage, such as young stocks, unprofitable stocks, small stocks, high-volatility stocks, extreme growth stocks, and distressed stocks.

In the context of understanding market anomalies in the stock market, the interaction with investor sentiment becomes a crucial aspect, given its significant role in driving these anomalies (Stambaugh et al., 2012). When investor sentiment is high, characterized by excessive optimism and positive attitudes towards the market, it can lead to overconfidence and overvaluation of assets. This overvaluation can cause stock prices to deviate from their fundamental values and potentially result in bubbles and extreme speculative behavior. Consequently, market anomalies like stock market overreaction can occur. High sentiment may cause investors to overreact to news, leading to temporary mispricing. Conversely, when investor sentiment is low, characterized by pessimism and negative attitudes towards the market, it can lead to undervaluation of stocks. Stambaugh, Yu, and Yuan (2012) demonstrated the greater profitability of long-short strategies following periods of high sentiment, suggesting that sentiment-driven overpricing is a primary source of these profits. Additionally, Baker, Wurgler, and Yuan (2012) provided international evidence of the forecasting power of investor sentiment by studying its impact on stock returns across various markets.

As the predictability of traditional sentiment measures on the aggregate stock market are of insignificant explanatory power, the importance of aligning an index with its purpose is emphasized by various researchers. While using the same sentiment proxies as proposed by Baker and Wurgler, Huang et al. (2015) introduced an alternative investor sentiment index. They departed from the conventional Principal Component Analysis (PCA) approach employed by Baker and Wurgler that essentially tries to extract the most dominant source of variation among all the proxies. Instead, Huang et al. incorporated the Partial Least Squares (PLS) method, introduced to finance by Kelly and Pruitt (2013, 2015), to capture and enhance relevant information in sentiment proxies, while eliminating a common noise component[1].

1 Both PCA and PLS are mathematical techniques used for dimensionality reduction, however their purposes and approaches differ. PCA emphasizes capturing variance and reducing dimensions, while PLS is designed to build predictive models while considering the covariance between variables. Through the alignment of sentiment proxies and the application of the PLS method, the sentiment index by Huang et al. has shown to have much greater predictive power for the aggregate stock market than existing sentiment indices have.

By incorporating the PLS method, the *aligned* sentiment index incorporates efficiently information that is relevant to the expected stock returns from the error or noise. As shown by forecast encompassing tests, the index has much greater predictive power than traditional sentiment proxies and the increased predictability holds, notably, both statistical and economic significance (Zhou, 2018).

Empirically, the aligned sentiment index predicts the aggregate stock market remarkably well and performs the best compared to the Baker and Wurgler Sentiment Index itself and other well-known macroeconomic predictors as described by Welch and Goyal (2008), such as short-term interest rate, dividend yield, and earnings-price ratio (Huang et al., 2015).

Conclusively, highlighting the significance of accurately capturing investor sentiment, Huang et al. (2015) unveil the aligned sentiment index by employing six sentiment proxies introduced in the Baker and Wurgler Sentiment Index (Baker and Wurgler, 2006; 2007). Notably, this index demonstrates a remarkable ability to negatively forecast aggregate stock market behavior; elevated sentiment today corresponds to lower future market returns.

2.8. Investor Sentiment and Overreaction

As previously discussed, investor sentiment plays a vital role in shaping market dynamics, with high sentiment leading to potential overpricing and low sentiment to potential undervaluation of assets. These sentiment-driven market behaviors have implications for understanding overreaction effects, as investor sentiment can contribute to the temporary mispricing observed during extreme market events. Delving further into the relationship of the overreaction effect, investor sentiment, and stock market returns, the paper by Piccoli and Chaudhury (2018) sheds light on how sentiment-driven overreactions may contribute to market inefficiencies and subsequent price reversals. The study explores how investor sentiment influences the magnitude and duration of overreactions to extreme market events and whether investor sentiment plays a role in exacerbating or dampening the effects of such events on stock prices. Their findings reveal that heightened sentiment can intensify market overreactions, prolonging their duration, while subdued sentiment might result in more transient reactions. In essence, the research highlights the intertwined relationship between investor sentiment and market reactions, underscoring its influence during turbulent market periods.

2.9. Research Hypotheses

Stock market overreaction and investor sentiment have been longstanding subjects of interest in financial literature. As illustrated in prior sections, researchers like Piccoli and Chaudhury (2018) have delved into the dynamic interplay between these two factors and their combined impact on market pricing and behavior. Building on these foundational studies, this research aims to further probe the relationship between investor sentiment and stock market overreaction, while introducing novel aspects that have not been previously explored.

H1: Overreaction and Subsequent Price Reversal in the Stock Market

H1a: There is a subsequent price reversal following a substantial stock price decline, indicating an overreaction in the Stock Market.

H1b: The subsequent three trading days after a substantial price drop exhibit positive abnormal returns.

Rationale: Sharp declines in stock prices can induce panic selling, leading to overreactions. Such overreactions are often followed by price reversals as market corrections take place, with the initial days potentially exhibiting a bounce-back effect.

H1c: The magnitude of stock price reversals, following a significant price drop, diminishes over time.

H1d: Accounting for the bid-ask spread does not influence the occurrence of price reversals.

Rationale: As the market starts to stabilize after an overreaction, the strength of the reversal trend may wane. This intrinsic dynamic is not significantly impacted by bid-ask spreads.

H1e: Market liquidity negatively affects the stock price reversals.

H1f: The size of companies (measured by market capitalization) weakens the magnitude of stock price reversals.

Rationale: Liquid markets and larger firms tend to have smoother price adjustments due to efficient price discovery and greater visibility, respectively, making them less prone to pronounced reversals.

H2: Duration and Magnitude of Overreactions

H2a: After an initial stock price decline, securities experience an extended period of subpar performance.

H2b: Following a stock price drop, securities exhibit negative cumulative returns over a period from the 4th trading day to the 20th trading day.

Rationale: The market's initial correction post a sharp decline might be followed by a prolonged phase of underperformance as investor sentiment remains bearish.

H2c: The intensity of the reversal of positive abnormal returns, observed from the 1st to the 3rd day after a substantial decline, weakens over time.

Rationale: The market's initial bullish correction response post an overreaction might be short-lived, giving way to more muted returns in the subsequent days.

H3: Interaction of Investor Sentiment with Overreaction Effect

H3a: During periods of high sentiment, there is a positive relationship between investor sentiment and CAR, particularly in the short term (Days 1-3). The greater the investor optimism, the more pronounced the overreaction effect becomes.

Rationale: High sentiment periods are marked by increased optimism, leading investors to react more significantly to news or events, thereby amplifying the overreaction effect.

H3b: During periods of low sentiment, the relationship between investor sentiment and CAR is attenuated, especially in the short term (Days 1-3). Pessimistic outlooks make investors more reluctant, dampening the overreaction effect.

Rationale: Low sentiment periods, characterized by caution or pessimism, induce a tempered reaction from investors to market news or events, thereby reducing the intensity of the overreaction effect.

H4: Interaction of Control Variables with Investor Sentiment

H4a: In high sentiment periods, control variables like EAR, SIZE, VOL, and D_{NYSE} *exert a stronger influence on CAR compared to periods of low sentiment. This means that their coefficients would be more significant and possibly larger in magnitude.*

Rationale: The heightened optimism during high sentiment periods can magnify the effects of these variables, leading to more pronounced market reactions.

H4b: In low sentiment periods, the impact of control variables on CAR is subdued, as investors are less responsive to the typical market cues represented by these variables.

Rationale: The cautious stance during low sentiment times can cause these control variables to have a diminished impact on market movements.

CHAPTER 3 DATA

This chapter provides a comprehensive overview of the data analyzed in this research. The data's sources, the specific characteristics of the stock markets from which it was drawn, and the nuances associated with these markets are detailed. Furthermore, specific data adjustments, excluding certain industry codes, are justified to ensure the research's precision and relevance.

3.1. Stock Market Data

The foundation of this research builds upon stock market data from the United States, specifically daily return data spanning two decades, from January 2002 to January 2022. This granular data set, primarily sourced from the Centre for Research in Securities Prices (CRSP) database, focuses on firms listed on the two primary U.S. stock exchanges: the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ).

Within the collected dataset, certain adjustments were essential to refine the focus of the analysis and mitigate potential distortions. Companies classified under SIC codes 6000 to 6800 are excluded from the study. These codes represent financial companies with unique financial structures and practices that could unintendedly skew the research outcomes. Similarly, companies categorized under the SIC code 9999 are excluded. This specific code denotes unidentified industries, and its inclusion could introduce unwarranted noise or ambiguity into the analysis. By making these exclusions, the dataset was streamlined to offer a more targeted and coherent examination of stock market overreactions and investor sentiments.

Further, within the preliminary stages of examining the dataset, certain inconsistencies were identified. Multiple listings of the same companies with distinct stock prices emerged, suggesting the presence of different stock classes, such as Class A and Class B. Recognizing the implications of these discrepancies, it was essential to refine the analysis methodology. Instead of broadly categorizing by the company name, which risked conflating different stock classes, the study adopted a unique identifier for each security. This adjustment ensured each stock class was distinctly treated, laying the foundation for an accurate and comprehensive assessment of stock market overreactions and investor sentiments.

3.2. Stock Market Characteristics

Before delving into the specific attributes of the NYSE and NASDAQ, it is essential to understand the broader backdrop against which these exchanges operate. These exchanges, while both pivotal in the U.S. stock market landscape, have unique features, histories, and listed firms. The ensuing sections provide a deep dive into these distinctions.

New York Stock Exchange (NYSE)

As one of the world's oldest and most renowned stock exchanges, the NYSE is home to a wide spectrum of businesses. It predominantly features blue-chip corporations from diverse sectors such as energy, finance, manufacturing, consumer goods, and healthcare. Renowned for attracting firms that prioritize steady growth and consistent dividends, it largely comprises enterprises with significant industry footprints.

National Association of Securities Dealers Automated Quotations (NASDAQ)

Contrastingly, the NASDAQ is globally recognized for its technological innovation. It predominantly lists companies emphasizing growth, especially those embedded in technology, biotechnology, and internet-based sectors. Due to its focus on breakthrough products, services, or technologies, the NASDAQ tends to witness higher volatility, attracting companies with disruptive innovations. As a result, it inherently carries a higher risk profile than the more stability-oriented NYSE.

The inherent differences between NYSE and NASDAQ manifest not only in the nature of their listed firms but also in market dynamics, such as volatility and liquidity. For instance, the stability-driven profile of NYSE companies typically results in lower price volatility. In contrast, NASDAQ, emphasizing growth and innovation, often witnesses sharper price movements.

Liquidity also underscores distinctions between the two exchanges. Generally, the NYSE offers a liquid trading environment due to its array of established firms attracting diverse investors. While NASDAQ does house some highly liquid tech giants, it also comprises companies with varied liquidity profiles, sometimes leading to significant market activity shifts.

The differences in market liquidity between these exchanges enable this paper to study the role of market liquidity in the reversal process from multiple perspectives. As mentioned by Cox and Peterson (1994), market liquidity impacts the reversal pattern, evidenced by 1) stronger reversals in less liquid markets, 2) amplified reversals in smaller firms compared to larger firms, and 3) the increasing liquidity of markets over time due to factors like heightened trading volumes, larger number of traders, and diminished transaction costs. Given the potential influence of market liquidity on price dynamics, this paper further examines its insights.

3.3. Research Period

From January 2002 to January 2022, this paper investigates a period characterized by a dynamic market environment. Within these two decades, the world experienced profound economic and financial implications, resulting in major policy responses and significant shifts in investor sentiment. Such events offer a rich context to understand investor behavior, particularly when sentiment becomes a dominant influencing factor.

The early 2000s witnessed markets grappling with the after-effects of the Dot-com Bubble's burst, presenting an opportunity to study investor behavior in the wake of significant downturns.

Subsequently, the Global Financial Crisis of 2007-2008 emerged as a critical disruption, offering a pertinent backdrop to investigate overreactions and market adjustments. The extensive monetary measures introduced, such as the U.S. Federal Reserve's quantitative easing, indelibly affected market dynamics.

Emerging from this crisis, the ascendancy of Big Tech companies like Apple, Amazon, and Google began to dominate the market narrative. Milestones like Apple's trillion-dollar valuation in 2018 underscored this trend. Concurrently, the increasing prevalence of algorithmic trading brought new dimensions to market dynamics.

However, 2020 introduced unforeseen challenges with the onset of the COVID-19 pandemic. The resulting global economic disruptions and the subsequent policy measures introduced periods of pronounced market volatility.

The timeline of this study also intersects with crucial non-financial events that have undeniably influenced global markets. Sociopolitical shifts, such as Donald Trump's 2016 election, escalating U.S.-China trade tensions, and the U.K.'s decision on Brexit, provide insights into the market's reactions to geopolitical uncertainties. Additionally, environmental crises, like the Tsunami in Japan in 2011, further highlight the market's sensitivity to a broad spectrum of global events.

Analyzing this period offers valuable insights into investor behavior, especially where investor sentiment is a significant factor, particularly during extreme market events. However, this paper does not examine the events in isolation; instead, it focuses on understanding how investor sentiment, influenced by these events, shapes the behavioral patterns in individual financial decision-making.

3.4. Investor Sentiment Data

3.4.1. Data Sources

The primary dataset for sentiment proxies originates from the website maintained by Jeffrey Wurgler. This site has compiled and updated data from July 1965 to June 2022, making it a rich source of historical sentiment data. The data is widely used in numerous studies such as Baker and Wurgler (2006, 2007, 2012), Yu and Yuan (2011), Baker et al. (2012), Stambaugh et al. (2012), and more.

While Wurgler's site provides a comprehensive set of sentiment-related data, it is essential to acknowledge that the foundational data originates from well-regarded institutions, notably the Centre for Research in Security Prices (CRSP) and various IPO databases.

3.4.2. Baker and Wurgler's Sentiment Proxies

Baker and Wurgler's sentiment index (2006; 2007) is influential in the study of market sentiment, utilizing several proxies to examine investor sentiment. The proxies and their underlying rationales are:

Closed-end Fund Discount (CEFD)

Closed-end funds issue a fixed number of shares, and their prices can deviate from their assets' net asset value (NAV). This deviation is the discount (or premium if the fund's price exceeds its NAV). The discount on closed-end funds can serve as a sentiment indicator because it is believed to reflect non-fundamental demand factors. When investor sentiment is high, the discount narrows (or even becomes a premium), and when sentiment is low, the discount widens.

NYSE Share Turnover (TURN)

This proxy is the ratio of trading volume to the number of shares listed. High turnover is generally associated with speculative trading or high investor attention. Higher turnover is often seen during periods of increased investor optimism or when non-informational trading (i.e., trading not based on new information about fundamentals) is more prevalent.

Number of Initial Public Offerings (NIPO)

More companies tend to go public during times of high investor sentiment or optimism because favorable market conditions make it easier for companies to raise capital at higher valuations. A high number of Initial Public Offerings (IPOs) indicates elevated investor sentiment, while a low number can indicate pessimism.

Average First-day Returns on IPOs (RIPO)

A significant positive first-day return on an IPO suggests strong investor demand and possibly over-optimism. When investor sentiment is high, IPOs tend to be more underpriced, leading to higher first-day returns.

Dividend Premium (PDND)

The dividend premium measures the difference between the average market-to-book ratios of dividend-paying and non-dividend-paying stocks. The intuition is that during high sentiment periods, younger, riskier, non-dividend-paying firms (often growth-oriented) are relatively overpriced compared to more mature, dividend-paying firms. Thus, a higher dividend premium indicates higher sentiment.

Equity Share in New Issues (EQTI)

This is the ratio of equity issues to firms' total equity and debt issues. When firms prefer issuing equity over debt, it might indicate that stocks are relatively overvalued (or that equity is "cheap" from the issuer's perspective). A high equity share in new issues can signify high investor sentiment as firms take advantage of favorable equity market conditions.

Baker and Wurgler argue that while each of these proxies has individual biases and imperfections, aggregating them into a composite index can extract the common component that reflects investor sentiment. This composite measure, they contend, provides a more reliable and robust indicator of market-wide sentiment than any individual proxy.

3.4.3. Missing NYSE Turnover Proxy

Baker and Wurgler's original work (2006, 2007) included the 'Share Turnover (TURN)' as a proxy for sentiment. However, they later decided to exclude it. The rationale for this exclusion, as provided by the authors, revolves around the significant changes in the meaning and implications of turnover in recent years (Wurgler, 2022). With the rise of institutional high-frequency trading and diversification across various platforms, turnover no longer holds the same sentiment-indicative value it once did. Given this insight, our research will follow their updated approach, focusing on the remaining five indicators.

3.4.4. Aligned Sentiment Index

Building upon the foundational work of Baker and Wurgler, Huang et al. (2015) present a distinct perspective on sentiment analysis. Their aligned sentiment index offers a novel approach to understanding investor sentiment, emphasizing the consistency of signals across various sentiment indicators. The data requisites for this index are mainly consistent with those of Baker and Wurgler.

In addition to the sentiment proxies, Huang et al. (2015) integrate aggregate stock market data into their methodology. Specifically, they compute the aggregate stock market return as the excess return determined by the continuously compounded logarithmic return on the S&P 500 index (inclusive of dividends) subtracted by the risk-free rate. Given that this paper builds upon the analysis by Huang et al. and focuses on the U.S. stock market, the S&P 500 will be used as a representative measure of the aggregate U.S. stock market in this study.

In this chapter, stock market data from the NYSE and NASDAQ, encompassing their sources and distinct characteristics, is discussed. The research period spans from 2002 to 2022, capturing major financial events. Investor sentiment data, primarily anchored on Baker and Wurgler's proxies, is explored, supplemented by Huang et al.'s study which introduces the aligned sentiment index.

CHAPTER 4 METHODOLOGY

The methodology chapter provides a comprehensive approach to analyzing investor sentiment in the stock market. The study initially outlines the calculation of stock returns, with specifically abnormal returns, essential for event study methodology. As the chapter progresses, the focus shifts towards data treatment, event selection, and ensuring the results' reliability and relevance. Further, the methodology aims to indicate how investor sentiment and market reactions intertwine, while providing perspective into sentiment determinations.

4.1. Stock and Abnormal Returns

This section delves into the methodologies employed to compute daily stock returns, abnormal returns that highlight event-specific impacts, and cumulative abnormal returns to aggregate these effects over time.

4.1.1. Simple and Log Returns

Given their intuitive nature, this study adopts simple returns, as these are particularly suitable for short-term analysis. Simple returns, representing the percentage change in stock price, are defined by:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where:

R_t *is the simple return on day t,*

P_t *is the stock price on day t, and*

P_{t-1} *is the stock price on the previous day.*

4.1.2. Abnormal Returns

Abnormal returns represent the deviation between the actual stock return and the expected return given prevailing market movements. In event study methodology, they serve as a tool to isolate the specific impact of a particular event on stock prices, excluding influences from overall market fluctuations.

Various methodologies compute abnormal returns, and one notable study by Cox and Peterson (1994) identifies several approaches. They discuss six ways to measure abnormal returns: two versions of the mean-adjusted returns approach based on pre-event means and on post-event means, two versions of the market model approach on either pre-event or post-event parameters, the market-adjusted approach, and the modified market-adjusted approach. In the modified market-adjusted approach the daily abnormal return is computed as the difference between the security's return and the product of an average of pre-event and post-event betas with the return on the market.

Among these methodologies, this research employs the modified market-adjusted approach as the primary method for calculating abnormal returns. The rationale behind this selection rests on two critical observations:

- **Stability of Betas**: As noted by Cox and Peterson (1994), this approach considers the stability of betas, making it a balanced approach between the pre and post event periods. Given that betas tend to be relatively stable and greater than one, this method can provide a more nuanced picture of abnormal returns without favoring either the pre or post event period.
- **Balanced Approach**: By using an average of the pre-event and post-event betas, this method effectively incorporates information from both periods, which might help in addressing potential concerns about structural shifts or regime changes around the event.

The modified market-adjusted approach is expressed mathematically as:

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

Where:
$AR_{i,t}$ *is the abnormal return for security* i *at time* t*,*
$R_{i,t}$ *is the return of security* i *at time* t*,*
$\bar{\beta}_i$ *is the average beta, derived from both pre-event and post-event periods, of security* i*,*
$R_{m,t}$ *is the market return at time* t*.*

4.1.3. Cumulative Abnormal Returns

Cumulative Abnormal Returns (CAR) represent the aggregate abnormal returns over a specified event window. The event window is a predefined period surrounding the event of interest, including days leading up to the event and days following it. By aggregating the daily abnormal returns, CAR offers insight into the total effect of the event over the entire window. This aggregation provides a more holistic understanding of the event's impact on stock prices beyond the daily fluctuations.

To calculate CAR, the daily abnormal returns (AR) for each day within the event window are simply summed up:

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

Where:
$CAR_{i,t}$ is the cumulative abnormal return for security i over the event window t time t,

$AR_{i,t}$ is the abnormal return of security i at time t,

$\sum_{t=t_1}^{t_2}$ is the summation of the abnormal returns from the start of the event window t_1 to its end t_2.

In this research, individual days subsequent to the decline are examined, specifically Day 1, Day 2, and Day 3. Additionally, cumulative results are analyzed over two specific intervals: Days 1 through 3 and Days 4 through 20. The selection of these specific windows and individual days is inspired by Bremer and Sweeney (1991), who delve into immediate short-term reactions to examine stock price reversals after significant price drops. Similarly, the cumulative period from Day 4 through 20 is based on the findings of Cox and Peterson (1994), who stress the importance of examining this longer span to capture more gradual market adjustments. These intervals and individual days provide a comprehensive perspective on both the immediate and extended market responses to the event.

4.1.4. Event Selection and Data Treatment

To ensure the integrity and reliability of the study's findings, certain data modifications were carried out:

Event Definition and Selection

Events in this study are defined as days where there is a stock price decline of 10% or more, adopting this 10% threshold as supported by previous research. The analysis is further limited to one event per day, per exchange to maintain statistical independence. Limiting the events in this manner ensures that each selected price drop is treated as an isolated occurrence, which is critical for ensuring the unbiasedness of the results. Having multiple events from the same exchange on the same day might introduce interdependencies, potentially skewing the findings.

This criterion is in alignment with methodologies employed in well-established studies on this topic, ensuring the focus remains on substantial market moves, thus enhancing the clarity and comparability of the findings.

The event selection process is crucial in determining the accuracy and representation of results in an event study. In the context of significant stock price declines, it is not uncommon to encounter multiple noteworthy declines on a singular trading day. How these events are selected can markedly influence the study's results.

Historically, researchers have employed an alphabetical selection strategy. However, this paper introduces an innovative randomized approach to event selection, aiming to rectify some inherent drawbacks of the traditional method.

Alphabetical Selection:

This conventional approach ordains that in circumstances with several pronounced price drops on a given trading day, companies are chosen based on their position in an alphabetical sequence. While this method might seem straightforward, it carries inherent biases that can influence the study's outcomes.

- **Overrepresentation**: Companies at the beginning of the alphabetical list (e.g., those starting with 'A') might be recurrently selected, especially if they undergo repeated price drops. This leads to a skewed representation of data, where patterns of a single or a few companies might disproportionately influence the study's outcomes.
- **Limited Diversity**: Conversely, companies appearing later in the alphabetical sequence might be rarely, if ever, picked, irrespective of the gravity of their price movements. This oversight can culminate in excluding diverse insights that these overlooked entities might otherwise contribute.

Randomized Selection:

Given the alphabetical selection's limitations, this research introduces a randomized event selection methodology to achieve a more balanced set of events. This method, while offering a more unbiased approach, also brings forth certain implications and considerations.

- **Uniform Representation**: Through randomization, each significant price decline, irrespective of the company it is associated with, gets an equal opportunity to be selected. This ensures that the data does not unintentionally favor any particular set of companies or industries, thus providing a more thorough overview of market reactions.
- **Diversity**: Randomized selection ensures that the dataset captures a mix of companies from various sectors, sizes, and characteristics. This diversity enriches the study by incorporating a broader range of market behaviors and reactions.
- **Reproducibility Concerns**: One inherent challenge with randomized selection is reproducibility. Different random samples might yield slightly varying results. To address this concern, this study conducts the analysis multiple times across different randomized samples. By comparing these repeated analyses, the study aims to ascertain the consistency of the findings, thereby enhancing the robustness of the conclusions.

Bid-Ask Bias Minimization

Stocks priced below $10 are more prone to distortions due to bid-ask spreads. In line with the results of Bremer and Sweeney (1991), this study omits stocks priced under $10 before the event to avoid such biases.

The process of data treatment and event selection is pivotal for the reliability of an event study. By considering factors such as bid-ask biases and event definition, this research ensures that the selected events and the subsequent data used are representative and unbiased.

4.1.5. Regression Model with Control Variables

To examine variation in reversals stemming from firm size, exchange listing, and trading volume, as well as to identify any potential overreaction effects, data from the two samples are pooled. The cumulative abnormal returns are then regressed against the abnormal return on day 0, a size index variable, trading volume, and respective dummy variables representing stock listings on the NYSE. The size index variable is the firm's percentile position when compared to all NYSE and NASDAQ firms, determined by the market equity value (market capitalization) six trading days before the event price drop. Additionally, the trading volume is represented by the natural logarithm of the event day's trading volume for the given security.

$$CAR_i = \gamma_0 + \gamma_1 EAR_i + \gamma_2 SIZE_i + \gamma_3 VOL_i + \gamma_4 D_{NSYE} + \varepsilon_i$$

Where:
$CAR_{i,}$ *is the cumulative abnormal return for security* i*,*
$EAR_{i,}$ *is the abnormal return of security* i *on the event day,*
$SIZE_{i,}$ *is the size index variable of security* i*,*
$VOL_{i,}$ *is the natural logarithm of the trading day of security* i *on the event day,*
$D_{NYSE,}$ *is the dummy variable, equal to 1 if the firm is listed on the NYSE and 0 if listed on the NASDAQ,*
$\varepsilon_{i,}$ *is the error term of security* i*.*

Subsequent analyses will ensure that all inferences made from regression models are robust, particularly by employing White's (1980) heteroskedasticity-consistent covariance matrix to account for any potential heteroskedasticity in the residuals.

4.2. Investor Sentiment

Investor sentiment plays a crucial role in shaping the dynamics of financial markets. Historically, researchers have sought robust methods to quantify this sentiment, aiming to predict market movements more accurately. Over the years, several methodologies have emerged, each with its own set of advantages and challenges. This section delves into two prominent sentiment indices, examining their foundational principles, methodologies, and effectiveness.

4.2.1. Baker and Wurgler Sentiment Index

In their seminal paper, Baker and Wurgler (2006) formulated a sentiment index (hereafter 'BW index') by employing principal component analysis (PCA) on a set of six distinct sentiment proxies. Before initiating the PCA process, each proxy was standardized to have a mean of zero and a standard deviation of one. This adjustment ensured that each proxy contributed equally to the sentiment index, devoid of any scaling disparities.

After standardization, the PCA identified the first principal component (PC1) as the most representative of the variance among the sentiment proxies. Baker and Wurgler adopted this PC1 as their sentiment index, conceptualizing it as a weighted sum of the six proxies, with the weights being the output of the PCA. In practical terms, the BW Index serves as a dynamic measure of investor sentiment: high values indicate optimism, whereas low values signal pessimism. By integrating the proxies in this manner, Baker and Wurgler achieved a consolidated sentiment measure that effectively minimized noise from individual proxies.

While the Baker and Wurgler sentiment index has been widely acknowledged for its ability to capture investor sentiment variations, as discussed earlier in the literature review, it is not without limitations. Notably, when the sentiment proxies used in the PCA demonstrate significant multicollinearity, the effectiveness of the PCA can be compromised where it does not optimally represent the shared variance among the predictors.

Multicollinearity is a recurring concern in econometrics and finance research. When predictors are closely correlated, accurately discerning the individual influence of each predictor on the dependent variable becomes challenging, potentially resulting in unstable coefficients and difficulties in model interpretation.

While the Baker and Wurgler sentiment index stands as a groundbreaking contribution to the realm of investor sentiment analysis, it is not without its challenges, especially when handling multicollinearity. This necessitated further exploration and refinement, leading to the inception of the Aligned Sentiment Index.

4.2.2. Aligned Sentiment Index

To address challenges in the Baker and Wurgler sentiment index, Huang et al. (2015) proposed the Aligned Sentiment Index (ASI), harnessing the Partial Least Squares (PLS) methodology. Recognized for effectively managing multicollinearity, PLS differentiates itself from the Principal Component Analysis (PCA) approach. While PCA primarily concerns itself with explaining variance in predictors, PLS emphasizes the covariance between predictors and the outcome. This distinction enabled Huang et al. to develop the Aligned Sentiment Index (referred to as the 'AS Index' hereafter).

A comparative evaluation between the Baker and Wurgler (BW) index and the AS Index demonstrated the superior predictive prowess of the latter. Specifically, Huang et al. found that the AS Index was more adept at predicting the aggregate stock market. Their findings revealed that the monthly in-sample and out-of-sample R^2 values in the Ordinary Least Squares (OLS) predictive regressions for the AS Index stood at 1.70% and 1.23% respectively. This is a marked improvement over the 0.30% and 0.15% observed with the BW index.

Given the AS Index's enhanced capability in capturing investor sentiment and its foundational principle that investor decisions are forward-looking, it emerges as an ideal tool for predicting future stock returns. This paper, in alignment with these principles, employs the AS Index. The rationale for this choice is anchored in the fact that stock market overreactions fundamentally stem from forward-looking investor decisions. Thus, the AS Index presents itself as the most suitable methodology to examine the role of investor sentiment in market overreactions.

It is essential to highlight that the AS Index is constructed from the perspectives of stock return predictability. As such, the methodology of this paper will follow the same rationale, emphasizing stock return predictability as a core principle in forming the AS Index.

4.2.3. Underlying Principles of the Aligned Index

It is crucial to understand the foundational assumptions and methodologies that underpin the Aligned Sentiment index. These assumptions serve as a guidepost for interpreting the index's predictions and understanding its inherent strengths. Based on the foundational work of Huang et al. (2015), which builds upon methods from Wold (1966, 1975) and Kelly and Pruitt (2013, 2015), several key assumptions form the basis for this analytical approach:

Expectation of Stock Returns

A primary assumption is that the one-period ahead expected excess stock return, influenced by investor sentiment, follows a standard linear relationship. This can be formally expressed as:

$$E_t(R_{t+1}) = \alpha + \beta S_t$$

Here, S_t represents the true but unobservable investor sentiment that is crucial for predicting stock returns.

Realized Stock Return

The actual stock return for a specific period can be broken down into its conditional expectation and an unpredictable component that is independent of S_t:

$$R_{t+1} = E_t(R_{t+1}) + \varepsilon_{t+1}$$
$$R_{t+1} = \alpha + \beta S_t + \varepsilon_{t+1}$$

In this representation, ε_{t+1} is an unpredictable error term that has no relation to S_t.

Investor Sentiment Proxies

Huang et al. introduce x_t – an N x 1 vector that includes individual investor sentiment proxies for a given time t. Following the approach of Baker and Wurgler (2006, 2007), these proxies consider six different sentiment proxies and as elaborated earlier in the paper, only five sentiment proxies will be utilized in this analysis due to the omitted share turnover measure.

Each sentiment proxy $x_{i,t}$ is assumed to have a factor structure:

$$x_{i,t} = \eta_{i,0} + \eta_{i,q} S_t + \eta_{i,2} E_t + e_{i,t}$$

Within this structure, S_t stands for the key investor sentiment that influences asset return predictions.
The coefficient $\eta_{i,1}$ reflects the sensitivity of sentiment proxy $x_{i,t}$ to changes in S_t.
Meanwhile, E_t represents the common approximation error present in all proxies, making it unrelated to returns.
Notably, $e_{i,t}$ specifies the unique error associated with the measure i.

The primary objective of these assumptions, as outlined by Huang et al., is to apply the factor structure to the sentiment proxies. This approach aims to efficiently estimate S_t, which represents the collective and intrinsic investor sentiment that remains unobservable. Simultaneously, it ensures the removal of E_t—the common approximation error present in all proxies—and $e_{i,t}$ from the estimation process.

This method underscores the importance of utilizing investor sentiment as a reliable predictor of asset returns, while mitigating the risks associated with approximation errors.

4.2.4. Aligned Index Methodology Using PLS

Huang et al. employed the Partial Least Squares (PLS) approach to effectively extract the true investor sentiment, S_t, while also filtering out the irrelevant component E_t. Unlike the Principal Component (PC) method, which does not always guarantee the removal of E_t, the core advantage of the PLS methodology lies in its capability to retrieve investor sentiment from the cross-sectional data. This is achieved by looking at its covariance with future stock returns, thereby finding a linear combination of sentiment proxies that is ideally suited for forecasting.

To operationalize this, Huang et al. employed a two-step Ordinary Least Squares (OLS) regression process:

1) Single Proxy Time-series Regression

For each sentiment proxy x_i, they conducted a time-series regression on a constant and the realized stock return R_t, that is expressed as:

$$x_{i,t-1} = \varphi_{i,0} + \varphi_i R_t + u_{i,t-1}$$

The resulting coefficient, $\varphi_{i,}$, from this regression indicates the responsiveness of each sentiment proxy $x_{i,t-1}$ to the sentiment S_{t-1}, which is essentially predicted using the future stock return R_t. Given that the expected return R_t is determined by S_{t-1}, it becomes evident that sentiment proxies are intrinsically linked to the expected stock returns.

Moreover, these proxies are not associated with unforeseen return shocks, as illustrated in the earlier equations. Thus, within the context of the initial time-series regression, the coefficient $\varphi_{i,}$ essentially quantifies the extent to which each sentiment proxy is influenced by the genuine investor sentiment.

2) Cross-sectional Regressions

In the subsequent stage of the analysis, the methodology involves executing cross-sectional regressions. In more specific terms, for every distinct time period, the study conducts a cross-sectional regression of the sentiment proxies $x_{i,t}$ using the factor loadings $\varphi_{i,}$ derived from the earlier time-series regression.

$$x_{i,t} = \omega_t + S_t^{PLS}\hat{\varphi}_i + v_{i,t}$$

The regression slope S_t^{PLS} in this context represents the inferred investor sentiment, hereafter referred to as the 'aligned sentiment index'. Within this equation, the preliminary loadings assume the role of primary independent variables, while the aligned sentiment, S_t^{PLS}, serves as the dependent variable.

Huang et al. employ the PLS technique to harness the interconnected nature of the given system. The objective of PLS is to extract the pivotal aligned sentiment factor S_t^{PLS}. The PLS method utilizes temporal data and the associated stock returns to streamline the extraction of the core sentiment S_t relevant for forecasting endeavors. Throughout this process, the method purposefully disregards both common and idiosyncratic components, such as E_t and $e_{i,t}$, considering them non-essential for the forecasting task.

In summary, the assumptions and methodologies behind the Aligned Sentiment Index provide a structured framework to extract genuine investor sentiment. By addressing the challenges of multicollinearity and leveraging the strengths of the PLS approach, the index offers a nuanced and effective tool for predicting market movements.

4.2.5. Classification of High and Low Sentiment Periods

To analyze investor behavior, especially overreactions, it is essential to understand shifts in sentiment dynamics. Overreactions are often more pronounced during changes in sentiment, emphasizing the need to categorize periods of distinctively high or low sentiment. This paper aims to examine investor overreactions during these transitions in investor sentiment.
To ensure a clear distinction between high and low sentiment periods, the Aligned Sentiment Index (AS Index) undergoes a standardization process. This adjustment gives the index a zero mean and a unit variance, enhancing the clarity of subsequent classifications.

Using the standardized Aligned Sentiment Index as a foundation, periods are segmented into high and low sentiment based on a straightforward yet impactful criterion: the index's median across the observed sample. Specifically:

- **High Sentiment Intervals**: These correspond to the months where the standardized AS Index exceeds its full-sample mean.
- **Low Sentiment Intervals**: These denote the months in which the standardized AS Index falls below its full-sample mean.

Applying the median as a classification criterion divides the sample almost evenly. This balanced split ensures a sufficient number of data points in both the high and low sentiment categories, enabling robust statistical analyses.

This method of classifying sentiment, inspired by Stambaugh et al. (2012), serves as a lucid and efficient means to distinguish between intervals of heightened and lowered investor sentiment. It is important to highlight that while the foundational methodology mirrors that of Stambaugh et al., our application pivots on the unique characteristics of the Aligned Sentiment Index.

4.2.6. Regression Model with Investor Sentiment

Understanding the relationship between investor sentiment and the cumulative abnormal returns provides key insights into market dynamics. This section introduces regression models to examine the role of investor sentiment on the reversal process, and the differences of the variables during shifting market sentiment periods.

Regression Model with Sentiment Variable

This model is essential for examining how investor sentiment might affect $CAR_{i,t}$. By introducing a continuous sentiment variable, S_t^{PLS}, the research captures the nuanced shifts in market sentiment. The sentiment variable measures is based on the Aligned Sentiment Index and examines the role of investor sentiment on the price reversal. This relationship is crucial because it acknowledges the possibility that investor reactions and, consequently, CAR, could vary based on the prevailing mood of the market. The general model with sentiment dummy is given by:

$$CAR_{i,t} = \gamma_0 + \gamma_1 EAR_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 VOL_{i,t} + \gamma_4 D_{NSYE,i} + \gamma_5 S_t^{PLS} + \varepsilon_{i,t}$$

Where:

$CAR_{i,t}$ *is the cumulative abnormal return for security* i *on time t,*

$EAR_{i,t}$ *is the abnormal return of security* i *on the event day,*

$SIZE_{i,t}$ *is the size index variable of security* i*,*

$VOL_{i,t}$ *is the natural logarithm of the trading day of security* i *on the event day,*

$D_{NYSE,i}$ *is the dummy variable for security* i*, equal to 1 if the firm is listed on the NYSE and 0 if listed on the NASDAQ,*

S_t^{PLS} *is the continuous sentiment score at time* t*, capturing the varying intensity of market sentiment,*

$\varepsilon_{i,t}$ *is the error term of security* i *on time* t*.*

Regression Model in High Sentiment Period

Diving into periods dominated by high sentiment offers insights into the behavior of control variables under optimistic market conditions. When the market is upbeat, investor behavior and reactions to events could diverge from neutral or pessimistic periods. For this regression, a filter is applied to focus solely on events that unfolded during high sentiment periods. The intent is to distinguish patterns or variations in the relationship between $CAR_{i,t}^{High}$ and its determinants, exclusive to these upbeat market scenarios.

The regression model for high sentiment periods is presented as:

$$CAR_{i,t}^{High} = \gamma_0 + \gamma_1 EAR_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 VOL_{i,t} + \gamma_4 D_{NSYE,i} + \varepsilon_{i,t}$$

This model allows for an exploration of how control variables interact and influence $CAR_{i,t}^{High}$ specifically during high sentiment periods.

Regression Model in Low Sentiment Period

On the flip side, analyzing periods characterized by low sentiment gains insights into investor dynamics under bearish or less optimistic market conditions. It is plausible that the relationship between $CAR_{i,t}^{Low}$ and its associated variables differs during periods when investors are more cautious or pessimistic. Applying a filter to concentrate on events from these low sentiment days provides a dedicated lens to capture any unique dynamics or interactions under lowered market sentiment.

The regression model for low sentiment periods is presented as:

$$CAR_{i,t}^{Low} = \gamma_0 + \gamma_1 EAR_{i,t} + \gamma_2 SIZE_{i,t} + \gamma_3 VOL_{i,t} + \gamma_4 D_{NSYE,t} + \varepsilon_{i,t}$$

This model allows for an exploration of how control variables interact and influence $CAR_{i,t}^{Low}$specifically during low sentiment periods.

Differentiation between High and Low Sentiment Periods

By segmenting the regression models based on sentiment (overall, high, low), the analysis offers a nuanced understanding of the role sentiment plays in shaping CAR and the interaction effects of control variables. The CAR is calculated for specific days, specifically days 1 through 3 and 4 through 20. The results from these regressions will shed light on whether the impact of control variables on CAR varies with the prevailing market sentiment and will also help determine if there are distinct patterns or differences in CAR across these specified days during high and low sentiment periods.

CHAPTER 5 RESULTS

In this chapter, the study delves into the dynamics of stock market reactions following significant price drops. It explores stock price reversals after these declines, investigates the influence of the bid-ask spread, employs regression models to discern the factors impacting abnormal returns, and incorporates an in-depth sentiment analysis to gauge the effect of investor sentiment on stock price overreactions and subsequent price reversals.

5.1. Stock Price Reversals after a Significant Price Decline

In the wake of significant price drops in the stock market, understanding the trajectory of stock prices becomes paramount. This section delves deep into the patterns of stock price movements, focusing on the behavior of stock prices after a substantial decline. By examining the abnormal returns during this period, we hope to gain a clearer perspective on market reactions and the extent of investor sentiment's role in these reversals.

5.1.1. The subsequent short-term price reversal

Table 1 showcases the average abnormal return values, accompanied by their respective t-values and significance levels, segregated based on listings from the NYSE and the NASDAQ stock exchanges. It captures the abnormal returns for the immediate aftermath of the price drop, covering Days 1, 2, and 3. The cumulative abnormal returns (CAR) for periods spanning Days 1 through 3 and Days 4 through 20 are also detailed. For a chronological perspective on the evolution of abnormal returns over a decade, the data is sectioned into four intervals, each of 5 years.

Given the random selection method employed, the analysis was executed three times. The values in Table 1 represent an average, pooling data from the three separate regressions.

The table presents the results derived from the analysis of abnormal returns following a notable one-day price drop exceeding 10%. Across the entire sample, there are no discernible significant positive cumulative abnormal returns in the short term, marking a deviation from the findings in the studies by Atkins and Dyl (1990), Bremer and Sweeney (1991), and Cox and Peterson (1994). This suggests the absence of a short-term price reversal subsequent to a significant price decline.

Table 1: Abnormal Returns of NYSE and NASDAQ securities Following a Significant One-Day Price Drop of more than 10%. *Daily abnormal returns are calculated individually for the three days subsequent to the one-day price decline. Cumulative abnormal returns are formed by summing the daily abnormal returns for the days 1 through 3 and days 4 through 20. Mean abnormal returns are presented, together with cross-sectional t-values. The event day of the large price decline is Day 0.*

Event Period	01-02'/12-06'	01-07'/12-11'	01-12'/12-16'	01-17'/12-21'
		NYSE Firms		
	N = 987	*N = 963*	*N = 967*	*N = 1,043*
Day 1	- 0.05% (- 0.34)	- 0.11% (- 0.64)	- 0.21% (- 1.06)	- 0.19% (- 0.95)
Day 2	0.14% (1.18)	0.03% (0.28)	0.06% (0.43)	- 0.03% (- 0.15)
Day 3	- 0.02% (- 0.14)	0.01% (- 0.01)	- 0.10% (- 0.78)	- 0.06% (- 0.43)
Days 1 – 3	0.01% (0.06)	- 0.07% (- 0.29)	- 0.29% (- 1.03)	- 0.34% (- 1.27)
Days 4 - 20	0.73% (2.13)	- 0.23% (- 0.58)	- 0.34% (- 0.81)	- 1.57%* (- 2.96)
		NASDAQ Firms		
	N = 1,200	*N = 1,090*	*N = 1,014*	*N = 1,052*
Day 1	0.16% (0.97)	0.54%* (2.46)	0.54%* (2.32)	1.00%* (2.97)
Day 2	0.07% (-0.06)	-0.13% (-0.81)	0.00% (-0.04)	0.68% (1.23)
Day 3	0.04% (0.32)	-0.03% (-0.17)	0.15% (0.86)	-0.28% (-1.04)
Days 1 – 3	0.25% (0.85)	0.30% (1.12)	0.62% (1.87)	0.61% (1.41)
Days 4 – 20	-0.29% (-0.67)	-0.02% (-0.20)	-0.65% (-1.36)	-0.91% (-1.25)

*Mean statistically significant from zero at a 5% significance level

For the securities listed on the NASDAQ, there are noticeable significant positive abnormal returns on the first day after the decline in three of the studied periods. Noteworthily, this trend suggests an ascending pattern in abnormal returns on Day 1 as time progresses.

In contrast, a substantial cumulative abnormal return spanning days 4 through 20 is identified in the final period for NYSE-listed stocks. In the analysis there was no evident price reversal (significant positive CAR from Days 1 to 3), indicating that the initial price recovery did not undergo a reversal. This observation contrasts with the findings by Cox and Peterson (1994), who documented that short-term price rebounds subsequent to a drop tend to reverse in the extended term.

5.1.2. The Influence of Bid-Ask Spread on Price Reversals

Efforts, such as implementing a minimum initial stock price of $10, have been initiated to counteract the impact of bid-ask variations. Despite these measures, the influence of these spreads on transaction-based returns remains significant. It is observed that a considerable number of closing transactions on the initial day (day 0) are quoted at bid prices, potentially due to heightened selling pressures. If, in subsequent days, securities exhibit an equal chance to close at bid or ask prices, a positive return might be seen. This phenomenon can be attributed to the bid-ask dynamics.

In the collected sample, the average bid-ask spread is noted at 0.6%. Interestingly, this metric witnesses an increase on the event day, peaking at 1.95%, and maintains a heightened level at 1.38% on the subsequent first day. These values inevitably prompt one to consider the bid-ask spread's potential impact on the previously discussed abnormal returns.

As observed, the bid-ask spread may play a role in influencing abnormal returns. To gain a clearer insight into this, an altered methodology was employed, which utilized the average of bid and ask prices instead of the transaction price. A comprehensive presentation of the findings from this revised approach can be found in Table 6 in the Appendix.

Within the context of the NASDAQ companies examined, the pronounced positive abnormal returns observed on the day following the event, spanning three distinct intervals, diminished in two of these intervals. Only the last interval maintained a significant positive return on the day following the event. Notably, this first-day abnormal return has increased by 0.4%. On the other hand, NYSE companies showed a steady pattern, with their long-lasting negative combined unusual returns mostly matching the first results. These changes, especially the decrease of certain strong reversal results, highlight an important point: the way bid and ask prices interact is not just by chance. They may have a real impact, as one of many factors, on how stock prices change direction.

5.1.3. Robustness Check

To ensure the robustness of the findings, a methodology inspired by Bremer and Sweeney (1991) was adopted. The analysis shifted its focus to a more stringent criterion, concentrating on instances with a notably steeper price decline.

When the threshold was adjusted to a 15% drop, there was a significant decrease in the number of events in the sample, descending from approximately 8,300 events to roughly 5,800. In this refined sample, the first day after the price decline revealed significant negative abnormal returns. This trend was particularly noticeable for stocks from both the NYSE and NASDAQ across two distinct ten-year periods from 2012 to 2022.

These findings illuminate the influential role of the chosen benchmark in determining the study's outcome. By comparing results from the initial 10% decline criteria to those of the more rigorous 15% threshold, it is evident that the outcome is sensitive to the selected parameters.

5.2. Analyzing Stock Price Reversals

This study delves into the complex dynamics of stock price reversals, aiming to understand how factors such as firm size, the exchange listing platform, and trading volume influence these movements. A central focus is to identify potential indications of market overreaction — where stock prices react more intensely than the associated event or news might suggest.

Table 2: Regression Model Explaining Abnormal Returns Following One-Day Price Declines.

Cumulative abnormal returns (CARs) are analyzed in relation to the event day abnormal return (EAR), a size index variable (SIZE), the natural logarithm of the trading volume on the event day (VOL), and a variable indicating if the firm is listed on the NYSE (D_NYSE). CARs span two distinct periods: the initial three days and the subsequent seventeen trading days post the pronounced price drop. Four distinct time frames are studied. Coefficient data is presented with t-values in brackets, and the approach utilizes White's (1980) method for ensuring consistent covariance in the presence of heteroskedasticity.

	Intercept	*EAR*	*SIZE*	*VOL*	D_{NYSE}	F-Value	R^2
Event Period	**CARs Measured over Days 1 - 3**						
Period 1	0.0516*	0.0169	-0.0129*	-0.0040*	0.0012	4.30*	0.010
	(4.03)	(1.52)	(-1.28)	(-3.89)	(0.35)		
Period 2	0.0747*	-0.0292	-0.0245*	-0.0063*	-0.0063	8.95*	0.000
	(4.72)	(-1.61)	(-2.17)	(-4.90)	(-1.63)		
Period 3	0.0599*	0.0038	-0.0377*	-0.0055*	-0.0038	5.16*	0.000
	(3.80)	(0.19)	(-3.06)	(-4.27)	(-0.98)		
Period 4	0.1056*	-0.0099	-0.0737*	-0.0104*	0.0035	11.82*	0.000
	(5.87)	(-0.36)	(-5.42)	(-6.75)	(0.77)		
	CARs Measured over Days 4 - 20						
Period 1	-0.0173	-0.0508*	-0.0071	-0.0005	0.0140*	3.62*	0.006
	(-0.68)	(-2.19)	(0.35)	(-0.24)	(2.09)		
Period 2	0.0078	0.0232	-0.0345	-0.0013	-0.0117	1.19	0.313
	(0.37)	(0.77)	(1.75)	(-0.73)	(-1.72)		
Period 3	0.0303	0.0140	-0.0131	-0.0034	0.0120*	1.6	0.171
	(1.31)	(0.56)	(0.70)	(-1.78)	(1.98)		
Period 4	0.0513	0.0281	-0.0661	-0.0056	-0.0135	2.01	0.091
	(1.40)	(0.56)	(1.89)	(-1.74)	(-1.38)		

*Mean statistically significant from zero at a 5% significance level

The examination of the relationship between certain coherent variables is shown in Table 2, where a detailed overview of the regression results is presented.

Firm size emerges as a significant factor in the analysis. Upon assessing the cumulative abnormal return (CAR) over the initial three days, the SIZE variable displays notable negative coefficients. This suggests that smaller stocks, often associated with wider bid-ask spreads and reduced liquidity, are more prone to experiencing pronounced short-term reversals.

The regression also provides insights into the impact of trading volume on the event day. A distinct negative coefficient indicates that increased trading volume on the event day has a negative effect on the CAR over the subsequent three days. This might be due to heightened trading activity reflecting intensified market sentiment or speculative trends. Such active trading can cause prices to deviate from their inherent values for a brief period, leading to potential adjustments in the days that follow as market actors reassess their stances based on fresh data or evaluations.

Further, no consistent relationship is found between the remaining variable, the exchange listing, and the degree of the price reversals. Similarly, this paper does not provide evidence to support the prevailing theory that more pronounced price drops lead to stronger reversals. The correlation between Abnormal Returns on the Event Day and subsequent CARs lacks statistical significance, prompting a reevaluation of current beliefs about price drop and reversal patterns.

Upon examining the cumulative abnormal returns spanning days 4 through 20, a clear negative correlation emerges during the initial period between the magnitude of the initial price decline and the subsequent long-term performance. This observation suggests that a greater price drop corresponds to a more pronounced long-term reversal. Contrarily, this discovery is inconsistent with the findings of Cox and Peterson (1994), who argued in their research that a larger initial decline suggests a more challenging future performance.

5.3. Investor Sentiment

Investor sentiment plays a pivotal role in financial markets, influencing stock prices, trading behavior, and market volatility. Traditional economic theories posit rational investor behavior, yet empirical studies highlight the deviations prompted by sentiment-driven decisions. Baker and Wurgler's foundational research underscored the impact of investor sentiment on stock markets. However, a deeper insight was offered by Huang et al. (2015) who refined the measurement and interpretation methodologies of investor sentiment. Building on this foundation, this study aims to examine the role of investor sentiment in stock price reversals following significant price declines.

The paper first presents a mathematical formulation of the Aligned Sentiment (AS) Index, providing a nuanced representation of investor sentiment. This is followed by an analysis of the temporal trends of the AS Index, emphasizing shifts in sentiment in response to significant market events. The core analysis centers on the impact of investor sentiment on Cumulative Abnormal Returns (CAR) using regression models that incorporate other control variables. The study concludes with a segmented regression analysis based on sentiment periods, investigating if investor behaviors exhibit variations during high and low sentiment phases. Through this approach, the research aims to shed light on the intricate role sentiment plays in dictating market dynamics.

5.3.1. Aligned Sentiment Index Using PLS Procedures

The Aligned Sentiment (AS) Index is derived using the Partial Least Squares (PLS) procedures, which aids in extracting the maximum variance from the predictors to the response variable. The mathematical representation is as follows:

$$S_t^{PLS} = -0.002\ CEFD_t + 0.007\ NIPO_t + 0.001\ RIPO_t - 0.012\ PDND_t + 0.441\ EQTI_t$$

Where:
S_t^{PLS} *is the Aligned Sentiment Index at time t,*
$CEFD$ *is the close-end fund discount rate at time t,*
$NIPO$ *is the number of IPOs at time t,*
$RIPO$ *is the first-day returns of IPOs at time t,*
$PDND$ *is the dividend premium at time t,*
$EQTI$ *is the equity share in new issues at time t.*

Each sentiment proxy represents a particular facet of market sentiment, and its coefficient indicates the degree of association with the overall sentiment index. For instance, a more significant coefficient for a given proxy suggests it has a more pronounced influence on the overall sentiment. It is interesting to note that, among the five proxies, EQTI is the most essential underlying component with a significant coefficient compared to the other proxies.

With a clear understanding of the ASI's mathematical formulation, a visual analysis becomes crucial. This offers a tangible representation of sentiment shifts over time.

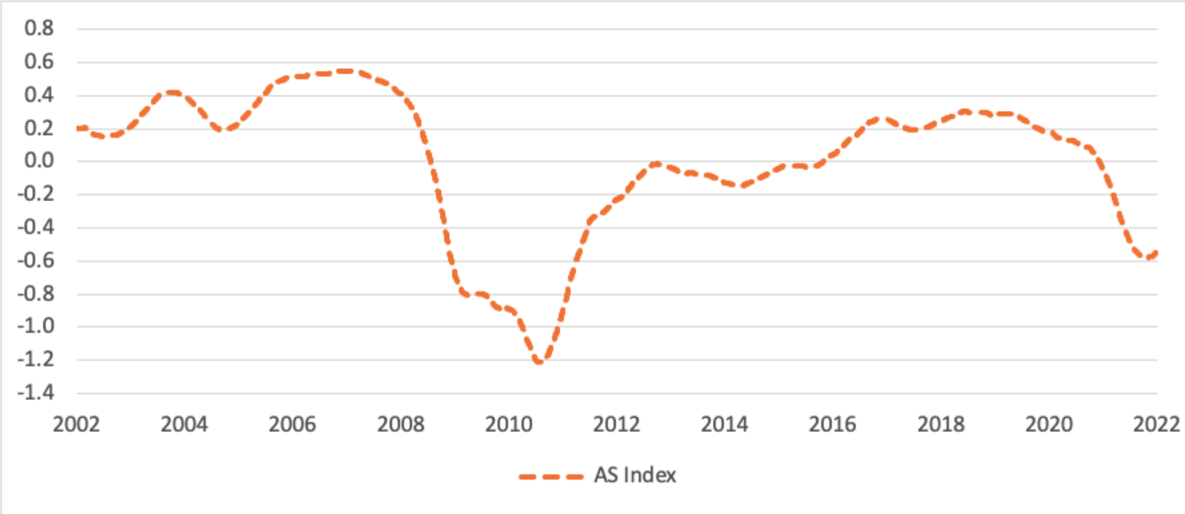

Figure 1. Temporal Evolution of the Aligned Sentiment Index (ASI) from 2002 to 2022.

In this figure, the Aligned Sentiment Index (ASI) is depicted. Values for individual sentiment proxies have been standardized, and the ASI is recalculated using the previously presented equation.

As depicted in Figure 1, the Aligned Sentiment Index (ASI) showcases marked fluctuations over the two-decade span from 2002 to 2022. This trend represents the ever-evolving investor sentiment in response to a plethora of market events and global incidents.

A distinct trough was observed in the period of 2008 to 2009, with the ASI plunging to its most negative point. This pronounced dip is consistent with the widespread financial turmoil experienced during the 2008 subprime mortgage crisis. The immediate aftermath saw a significant decline in investor sentiment, influenced by the global recession, the collapse of major financial institutions, and a decline in consumer wealth. However, after this crisis, a rapid resurgence in sentiment was evident by 2010, indicative of market recoveries and stabilizing economic conditions.

Furthermore, a noticeable decline is once again present around 2020. This drop can be attributed to the COVID-19 pandemic's onset, a global health crisis with far-reaching economic implications. The uncertainty and disruptions caused by the pandemic, combined with the implementation of widespread lockdowns and a temporary halt in business operations, led to a bearish market sentiment. As seen in the graph, the sentiment has yet to fully recover to its pre-pandemic levels by 2022, suggesting the long-term impact of the crisis on investor confidence.

The cyclical nature of the ASI, evident from the peaks and troughs, underscores the responsiveness of investor sentiment to significant events, whether economic, political, or health-related. Such insights from the index are instrumental in understanding the broader market dynamics and predicting potential future shifts in investor behavior.

While the visual trends provide an overview of sentiment shifts, a more in-depth statistical approach is required to discern the direct impact on stock prices. This leads us to a detailed regression analysis.

5.3.2. Regression Analysis Using the Aligned Sentiment Index

To gauge the explanatory power of the Aligned Sentiment Index (ASI) in predicting stock price reversals post notable price declines, a regression model is employed. The Cumulative Abnormal Returns (CAR) serves as the dependent variable, with ASI and other control variables as independent variables. In Table 3, the results from the regression model are presented.

Table 3: Regression Analysis of Cumulative Abnormal Returns (CARs) with Aligned Sentiment Index (ASI) and Control Variables.

Cumulative abnormal returns (CARs) are analyzed in relation to the event day abnormal return (EAR), a size index variable (SIZE), the natural logarithm of the trading volume on the event day (VOL), and a variable indicating if the firm is listed on the NYSE (D_NYSE). The sentiment variable S_t^{PLS} is added to examine the relationship with the short- and medium term potential price reversals.. CARs span two distinct periods: the initial three days and the subsequent seventeen trading days post the pronounced price drop. Four distinct time frames are studied. Coefficient data is presented with t-values in brackets, and the approach utilizes White's (1980) method for ensuring consistent covariance in the presence of heteroskedasticity.

	Intercept	*EAR*	*SIZE*	*VOL*	D_{NYSE}	S_t^{PLS}	F-Value	R^2
Event Period			**CARs Measured over Days 1 - 3**					
Period 1	0.0488*	0.0272	0.0127	-0.0041	-0.0031	0.0288	4.41*	0.009
	(3.65)	(1.95)	(0.99)	(-3.47)	(-0.79)	(1.63)		
Period 2	0.0607*	-0.0374*	0.0225	-0.0054	-0.0013	0.0452	6.47*	0.019
	(3.99)	(-2.28)	(1.93)	(-4.29)	(-0.32)	(1.59)		
Period 3	0.0445*	0.0025	0.0201	-0.0036	-0.0054	0.0141	1.76	0.006
	(2.18)	(0.12)	(0.99)	(-1.86)	(-1.29)	(0.82)		
Period 4	0.134*	-0.0423	0.0787*	-0.012	-0.0211	0.0555	2.43	0.034
	(2.81)	(-0.85)	(3.20)	(-2.84)	(-0.47)	(0.68)		
			CARs Measured over Days 4 - 20					
Period 1	-0.0171	-0.0503*	-0.0313	0.0028	0.1068	-0.0394	1.72	0.004
	(-0.71)	(-2.25)	(-1.13)	(1.26)	(1.72)	(-1.39)		
Period 2	0.0354	0.0194	0.0599*	-0.0052*	-0.0012	-0.0055	2.13	0.007
	(1.40)	(0.71)	(2.85)	(-2.47)	(-0.18)	(-1.11)		
Period 3	0.0096	0.0238	0.0487	-0.0013	0.0576	-0.0213	0.48	0.001
	(0.37)	(0.90)	(0.24)	(-0.64)	(0.95)	(-0.80)		
Period 4	0.0414	0.0579	0.0839*	-0.0056	-0.0019	0.0133	2.68*	0.007
	(1.10)	(1.29)	(3.26)	(-1.84)	(-0.21)	(0.83)		

*Mean statistically significant from zero at a 5% significance level

The only significant control variables for the short-term price reversal appear to be 1) the magnitude of the abnormal return on the event day (EAR) for the second period and 2) the size index variable (SIZE) in the fourth period.

As for the sentiment variable (S_t^{PLS}), it displays a consistent positive relationship with the magnitude of a price reversal after a severe price decline. However, this relationship was not found to be statistically significant. While the short-term analysis provides immediate insights, it is equally essential to understand sentiment's role over extended periods. This extended view can highlight deeper, more systemic market behaviors.

Delving into the results from an extended perspective reveals some pronounced dynamics. In the first period of the longer duration, we observed that the event's abnormal return (EAR) underwent a discernible negative shift. This indicates that, following a significant price drop, stocks tend to experience further depreciation, suggesting a continuation of the bearish trend.

In the second period, we found an interesting interplay between volume and stock price reversals. The volume of trades, represented by the 'VOL' variable, displayed a negative association with the Cumulative Abnormal Returns (CARs). This could be interpreted as a decrease in trading volume being correlated with a stabilization or potential uptick in stock prices. This trend might be indicative of the market sentiment cooling off after the initial reaction to a notable price drop.

By the fourth period, the size index variable emerges as a significant positive predictor. This suggests that larger firms, or perhaps those with a more considerable market capitalization, experience a more pronounced price reversal after a severe drop. This could be due to institutional investors considering such firms as safer bets during turbulent times, leading to increased buying activity.

The sentiment index, represented by S_t^{PLS}, while consistently showing a positive correlation with price reversals, does not assert itself as a significant predictor over the extended period. This suggests that while investor sentiment might have immediate short-term implications, its effect tends to diminish in the long run.

In conclusion, the longer-term analysis paints a nuanced picture of the market's response to significant price declines. While immediate reactions are influenced by the magnitude of the decline and investor sentiment, as time progresses, factors like trading volume and company size begin to assert their influence. However, while some variables exhibit pronounced effects in specific periods, the sentiment index (S_t^{PLS}) does not consistently manifest as a strong predictor in the periods studied.

5.4. Segmented Regression Analysis Based on Sentiment Periods

Investor sentiment, often deemed as the collective mood or attitude of market participants towards the financial market, wields a significant influence on stock prices and market behaviors. Recognizing the impact of sentiment, this analysis employs a segmented regression approach, segregating data into distinct high and low sentiment periods. By doing so, we aim to discern the differential effects of investor sentiment on cumulative abnormal returns (CARs) and understand how varying degrees of sentiment influence market anomalies.

This segmented approach provides a comprehensive outlook, allowing for a nuanced examination of how market reactions and anomalies shift in tandem with prevailing investor sentiment. In the following sections, we will delve deeper into the regression results for each of these sentiment periods, drawing insights from the obtained coefficients and their broader market implications.

5.4.1. High Sentiment Period

In high sentiment periods, investor optimism and enthusiasm are at their peak, and the propensity to take on risks is elevated. The results from our segmented regression shed light on how these heightened sentiments influence market anomalies.

Days 1 - 3: Immediate Market Reaction

Period 1: The intercept, significant at 0.0544, suggests a general upward trend in returns. This could be an initial bullish reaction, possibly driven by the "buy-the-dip" mentality prevalent among optimistic investors. Concurrently, the significant negative coefficient for VOL (-0.0036) suggests that stocks with higher trading volumes face a slight decline in CARs. This could indicate that high trading activity, possibly due to panic selling after a price drop, tends to suppress immediate rebound potential.

Period 2: The significant negative coefficient for SIZE (-0.0085) is interesting. Larger firms experiencing a more pronounced drop in CARs might be due to their high visibility in the market. When sentiment is high, any negative news or price drops concerning prominent firms might be magnified, causing a sharper decline.

Period 4: The positive coefficient for SIZE (0.0865) indicates a reversal from Period 2. Larger firms now benefit from higher CARs. This suggests that after the initial shock and selling pressure, investors might recognize the inherent value in larger, more stable firms, leading to a buying surge. Additionally, the consistent negative impact of VOL (-0.0137) could be a reflection of high volatility often being associated with risk, which, despite high sentiment, could deter some investors.

Table 4: Regression Model Explaining Abnormal Returns Following One-Day Price Declines in Periods of High Sentiment.

Cumulative abnormal returns (CARs) are analyzed in relation to the event day abnormal return (EAR), a size index variable (SIZE), the natural logarithm of the trading volume on the event day (VOL), and a variable indicating if the firm is listed on the NYSE (D_NYSE). CARs span two distinct periods: the initial three days and the subsequent seventeen trading days post the pronounced price drop. Four distinct time frames are studied. Coefficient data is presented with t-values in brackets, and the approach utilizes White's (1980) method for ensuring consistent covariance in the presence of heteroskedasticity.

	Intercept	***EAR***	***SIZE***	***VOL***	D_{NYSE}	**F-Value**	R^2
Event Period			**CARs Measured over Days 1 - 3**				
Period 1	0.0544*	0.0234	0.0065	-0.0036*	-0.0025	4.83*	0.007
	(4.31)	(1.76)	(0.49)	(-2.94)	(-0.65)		
Period 2	0.1104*	-0.0049	0.0206	-0.0085*	-0.0010	3.80*	0.044
	(3.75)	(-0.23)	(1.10)	(-3.60)	(-0.16)		
Period 3	0.1016*	0.0222	0.0422	-0.0082*	0.0006	2.86*	0.043
	(2.98)	(0.34)	(1.30)	(-2.72)	(0.07)		
Period 4	0.1483*	-0.0706	0.0865*	-0.0137*	-0.0061	2.82*	0.042
	(2.67)	(-1.17)	(3.06)	(-2.69)	(-1.19)		
			CARs Measured over Days 4 - 20				
Period 1	-0.0248	-0.0451*	-0.0227	0.0021	0.0097	1.57	0.003
	(-1.06)	(-2.01)	(-0.91)	(1.03)	(1.59)		
Period 2	0.0021	-0.0467	0.0273	-0.0035	0.0209	3.46	0.013
	(0.06)	(-1.42)	(0.89)	(-1.17)	(1.86)		
Period 3	0.0316	0.0217	0.0066	-0.0040	0.0174	0.61	0.006
	(0.67)	(0.39)	(0.15)	(-1.02)	(1.26)		
Period 4	0.0347	0.0399	0.1037*	-0.0066*	0.0093	3.97*	0.012
	(0.89)	(0.84)	(3.45)	(-2.06)	(0.98)		

*Mean statistically significant from zero at a 5% significance level

Days 4 - 20: Extended Market Reaction

Period 1: The significant negative coefficient for CAR (-0.0451) might reflect a corrective phase, where the initial enthusiasm wanes, leading to a recalibration of stock prices.

Period 4: The positive and significant coefficient for SIZE (0.0357) reiterates the preference for larger firms in high sentiment periods. Over extended periods, larger firms, with their established market positions and stability, could be viewed as safer bets, especially if the broader market starts showing signs of volatility or uncertainty.

Interpretation for High Sentiment Period

The data underscores the dynamic nature of investor behavior during high sentiment periods. The immediate reaction to price drops is mixed, with high trading volume acting as a deterrent to positive CARs and larger firms showing both vulnerability and resilience in different timeframes. As we move beyond the immediate aftermath, the value proposition of larger firms becomes more pronounced, echoing the hypothesis that SIZE, among other control variables, would exert a stronger influence during high sentiment periods. While not all coefficients aligned perfectly with expectations, the overarching theme that heightened optimism can lead to pronounced market reactions is evident.

Following the examination of market dynamics during periods of high investor sentiment, the subsequent section delves into the complexities of market reactions during periods characterized by low investor sentiment, uncovering the distinct patterns that emerge in a more cautious market atmosphere.

5.4.2. Low Sentiment Period

During periods of low investor sentiment, the market is typically dominated by pessimistic views, often leading to heightened caution and risk aversion among participants. Such periods provide a contrasting backdrop to the high sentiment phase, enabling a deeper understanding of how market anomalies manifest in bearish environments. As investors navigate this cautious landscape, their reactions to market events can offer profound insights into the interplay between sentiment and market anomalies. In this section, we will dissect the regression results for the low sentiment period, revealing how different factors influence cumulative abnormal returns (CARs) and exploring potential explanations behind these patterns.

Days 1 - 3: Immediate Market Reaction

Period 1: The intercept is significant with a value of 0.0157. This indicates an inherent effect during the initial days, independent of the explanatory variables. The trading volume (VOL) on the event day stands out with a negative coefficient of -0.0082. This suggests that for stocks experiencing higher trading volumes, there's a tendency for negative CARs in the immediate aftermath. An interpretation could be that increased trading volumes during periods of low sentiment might reflect heightened investor anxiety or potential market overreactions, leading to amplified negative CARs.

Period 2: The intercept is once again significant, with a value of 0.0404, pointing towards a baseline effect. The event abnormal return (EAR) presents a significant negative coefficient of -0.0617. This implies that stocks with stronger positive abnormal returns on the event day tend to have more pronounced negative CARs in the short-term following the event. A potential explanation might be that during low sentiment periods, investors could be more skeptical or wary of stocks showing outsized gains, leading to subsequent sell-offs. Moreover, VOL remains consistently influential, further reinforcing the notion of trading volume being an essential factor during these periods.

Days 4 - 20: Extended Market Reaction

Period 2: The SIZE of the firm becomes particularly relevant during this extended period. With a positive coefficient of 0.0617, the data suggests that larger firms tend to display better CARs in this timeframe. One plausible interpretation is that during low sentiment periods, investors might gravitate towards larger firms perceived as more stable and resilient. The inherent diversification, broader operational capacity, and substantial resources of bigger firms may provide a safety net, making them a more appealing investment option during prolonged downturns or market uncertainties.

Interpretation for Low Sentiment Period:

During times of low sentiment, trading volume plays a consistent and significant role, especially in the short term, reflecting the market's collective mood and potential overreactions. The initial days post-event show that stocks with high positive abnormal returns might not necessarily be in favor, potentially due to increased investor scrutiny or skepticism. As we move to a longer timeframe, the size of a firm emerges as a pivotal factor, indicating a shift in investor strategy to prioritize stability and long-term resilience. The results from this low sentiment period underscore the complexity of market behavior during downturns and the multifaceted strategies adopted by investors in such climates.

Table 5: Regression Model Explaining Abnormal Returns Following One-Day Price Declines in Periods of Low Sentiment.

Cumulative abnormal returns (CARs) are analyzed in relation to the event day abnormal return (EAR), a size index variable (SIZE), the natural logarithm of the trading volume on the event day (VOL), and a variable indicating if the firm is listed on the NYSE (D_NYSE). CARs span two distinct periods: the initial three days and the subsequent seventeen trading days post the pronounced price drop. Four distinct time frames are studied. Coefficient data is presented with t-values in brackets, and the approach utilizes White's (1980) method for ensuring consistent covariance in the presence of heteroskedasticity.

	Intercept	***EAR***	***SIZE***	***VOL***	D_{NYSE}	**F-Value**	**R^2**
Event Period			**CARs Measured over Days 1 - 3**				
Period 1	0.0157*	0.0383	0.0562	-0.0082*	-0.0043	1.13	0.008
	(2.03)	(0.58)	(1.12)	(-2.76)	(-0.87)		
Period 2	0.0404*	-0.0617*	0.0284	-0.0046*	-0.0015	4.95*	0.015
	(2.32)	(-2.64)	(1.90)	(-3.06)	(-0.29)		
Period 3	0.0167	-0.0043	0.0116	-0.0015	-0.0064	0.58	0.002
	(0.63)	(-0.25)	(0.48)	(-0.62)	(-1.31)		
Period 4	0.0434	0.0678	0.0214	-0.0037	0.0134	1.04	0.013
	(1.19)	(1.13)	(0.86)	(-1.28)	(1.42)		
			CARs Measured over Days 4 - 20				
Period 1	-0.0567	-0.0563	-0.0248	-0.0078*	-0.0041	2.93*	0.011
	(-0.58)	(-1.63)	(-0.57)	(-3.42)	(-1.01)		
Period 2	0.0466	0.0599	0.0617*	-0.0050	-0.0113	1.75	0.009
	(1.47)	(1.54)	(2.24)	(-1.83)	(-1.35)		
Period 3	0.0000	0.0243	0.0046	-0.0003	0.0029	0.19	0.001
	(0.00)	(0.81)	(0.20)	(-0.13)	(0.43)		
Period 4	0.1297	0.0759	0.0714	-0.0089	-0.0414	1.11	0.008
	(1.00)	(0.63)	(1.47)	(-0.88)	(-1.53)		

*Mean statistically significant from zero at a 5% significance level

Alignment with Expectations

Our hypothesis posited that during low sentiment periods, the impact of control variables on CAR would be subdued, suggesting that investors might be less responsive to the typical market cues represented by these control variables. The rationale was based on the cautious stance investors would take during these times, potentially causing these variables to have a diminished impact on market movements.

The observed data does, to some extent, align with our hypothesis. Specifically, while trading volume shows an immediate effect, its impact appears to be more related to a reflection of the prevailing investor sentiment than a typical market cue. This suggests that investors may be reacting more to the collective mood than to the standard cues that the volume typically provides.

The influence of the firm size in the extended reaction period also points towards a focus on stability and resilience rather than typical market dynamics. Larger firms' perceived stability could be seen as a safety net during these cautious times, further supporting the hypothesis that standard market cues might have diminished influence.

5.4.3. Discussion and Comparison with High Sentiment Period Regression

This section contrasts market reactions during high sentiment periods with those observed during periods of neutral or low sentiment, shedding light on the nuances of investor behavior in differing sentiment climates.

Immediate Market Reaction

- High Sentiment: The market appeared more responsive to event-driven cues in the high sentiment period, with trading volume taking a leading role in determining immediate CARs. Positive news or events seemed to be magnified, leading to significant positive CARs.
- Low Sentiment: During low sentiment periods, the market seemed to display a heightened sensitivity to negative news. Stocks that exhibited marked declines continued to experience negative CARs, with the immediate reaction appearing to be more pronounced, possibly reflecting increased investor anxiety or potential overreactions.

Extended Market Reaction:

- High Sentiment: Firms of all sizes appeared to benefit during high sentiment periods. Notably, smaller firms experienced more pronounced positive CARs, indicating an optimistic outlook from the market and a willingness to invest in riskier stocks.
- Low Sentiment: In contrast, during the low sentiment periods, larger firms seemed to be perceived as more stable, showing better CARs over extended periods.

5.4.4. Discussion and Comparison with Previous Research

The findings to some extent align with existing research that emphasizes the impact of investor sentiment on market anomalies. Notable observations include:

Consistency with Prior Research

Earlier studies, including those by Stambaugh et al. (2012), have underscored how investor sentiment can amplify market reactions, both in positive and negative directions. The results from the high sentiment periods, especially the amplified positive CARs, seem consistent with their findings.

Discrepancies Observed and Potential Reasons for Discrepancies

Some earlier research, including those by Stambaugh et al. (2012), suggested that investor sentiment might have a uniform impact across firms. However, the current study indicates a distinction based on firm size, especially evident during low sentiment periods. Differences observed might arise due to various factors, including the chosen time frame of this study, as it only examines two decades of time, the specific U.S. market or region under investigation, or possibly evolving investor behaviors over time.

Implications

- For Investors: Recognizing the pronounced impact of collective investor sentiment might be instrumental in crafting informed investment strategies, particularly during sentiment extremes.
- For Policymakers: Identifying potential market volatilities or instabilities during low sentiment phases might be crucial for devising appropriate market stabilization measures.
- For Future Research: The nuanced results highlight the importance of considering firm size as a significant variable when dissecting market anomalies amidst different sentiment conditions.

CHAPTER 6 CONCLUSION

In conclusion, this study has undertaken a comprehensive examination of stock price reversals following significant declines and the complex role of investor sentiment in such reversals. The investigation into the patterns emerging after noteworthy downturns in stock prices has revealed that market responses are intricate and can vary notably between exchanges such as NYSE and NASDAQ, with NASDAQ stocks showing more consistent positive abnormal returns immediately after a price drop.

The study has demonstrated that the bid-ask spread dynamics and the size of the firm play substantial roles in the behavior of stock price reversals, with smaller stocks and increased trading volume being linked to more pronounced short-term reversals. Interestingly, while the Aligned Sentiment (AS) Index showed a positive correlation with the magnitude of price reversals, its influence was not statistically significant in the long term, suggesting the transient impact of investor sentiment on market adjustments.

Segmented regression analysis has offered additional insights, revealing that the immediate market reactions to stock price declines are more pronounced during high sentiment periods, particularly with positive events, while in low sentiment periods, there is a tendency for the market to react strongly to negative news, possibly due to investor overreaction or anxiety. Over longer periods, high sentiment seems to favor smaller firms with more pronounced positive cumulative abnormal returns (CARs), whereas larger firms tend to perform better during low sentiment periods, likely due to their perceived stability.

By weaving together the various strands of market data, firm-specific characteristics, and the psychological undercurrents of investor sentiment, this thesis underscores the multifaceted nature of stock market behavior. While immediate reactions to price declines are somewhat influenced by sentiment, the eventual market stabilization appears to be governed by more substantive factors such as firm size and trading volume. Therefore, the findings suggest that while sentiment can sway immediate market reactions, its effects are less persistent.

Ultimately, based on the evidence from the two decades examined, there is not sufficient support for the hypothesis of a persistent overreaction in the stock market. The results of this paper, while extensive, are subject to its inherent limitations, including the random selection of events for study and the use of data spanning only 20 years—a period notable for numerous significant market events that could potentially skew the results.

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APPENDIX

Table 6: Abnormal Returns of NYSE and NASDAQ securities Following a Significant One-Day Price Drop of more than 10% Based on the Average of the Bid and Ask price.

Event Period	**01-02'/12-06'**	**01-07'/12-11'**	**01-12'/12-16'**	**01-17'/12-21'**
		NYSE Firms		
	N = 987	*N = 963*	*N = 967*	*N = 1,043*
Day 1	0.13%	-0.21%	-0.12%	-0.24%
	(0.87)	(-1.36)	(-0.72)	(-1.33)
Day 2	0.02%	0.14%	0.14%	-0.32%
	(0.21)	(1.07)	(1.06)	(-1.64)
Day 3	0.06%	0.04%	-0.12%	0.09%
	(0.61)	(0.31)	(-0.97)	(0.59)
Days 1 – 3	0.16%	-0.03%	-0.11%	-0.52%
	(0.83)	(-0.15)	(-0.43)	(-1.83)
Days 4 – 20	0.36%	0.28%	-0.35%	-1.64%*
	(1.07)	(0.67)	(-0.83)	(-3.34)
		NASDAQ Firms		
	N = 1,200	*N = 1,090*	*N = 1,014*	*N = 1,052*
Day 1	0.30%	0.15%	0.30%	1.39%*
	(1.77)	(0.75)	(1.24)	(2.57)
Day 2	-0.15%	-0.19%	0.06%	0.65%
	(-1.12)	(-1.29)	(0.35)	(1.08)
Day 3	0.13%	0.09%	0.18%	-0.14%
	(1.01)	(0.61)	(0.73)	(-0.36)
Days 1 – 3	0.26%	0.05%	0.43%	0.75%
	(1.10)	(0.16)	(1.23)	(1.45)
Days 4 – 20	-0.64%	0.24%	-1.25%*	-0.73%
	(-1.36)	(0.48)	(-2.69)	(-1.01)

*Mean statistically significant from zero at a 5% significance level