UNIVERSITY OF GDAŃSK - FACULTY OF ECONOMICS

Honecker, Lukas Udo

Field of science: Social Sciences
Scientific discipline: Economics and Finance

The Role of Investor Sentiment in Moderating the Impact of Exogenous Shocks on Stock Prices

PhD dissertation
prepared under the supervision of
Dr hab. Anna Blajer-Gołębiewska, prof. UG
Supporting supervisor: Dr Sabina Nowak

Sopot 2025

STRESZCZENIE

Rola nastrojów inwestorów w moderowaniu wpływu szoków egzogenicznych na ceny akcji

Lukas Udo Honecker

Problem badawczy podjęty w niniejszej dysertacji dotyczy roli nastrojów inwestorów w kształtowaniu cen akcji w czasie szoków egzogenicznych. Badanie ma na celu pogłębienie wiedzy na temat znaczenia specyficznych dla przedsiębiorstw nastrojów inwestorów opartych na zmiennych rynkowych jako moderatorów wpływu szoków egzogenicznych na ceny akcji. Szokami egzogenicznymi analizowanymi w tej pracy są trzy istotne wydarzenia, które miały miejsce podczas wybuchu i początkowego rozprzestrzeniania się pandemii COVID-19 w 2020 r.: (1) ogłoszenie pierwszego potwierdzonego pozytywnego przypadku COVID-19 w USA, (2) ogłoszenie COVID-19 jako stanu zagrożenia zdrowia publicznego w USA oraz (3) oficjalna deklaracja Światowej Organizacji Zdrowia o COVID-19 jako globalnej pandemii. W badaniu wykorzystano dane 367 amerykańskich spółek wchodzących w skład indeksu S&P 500. Skonstruowano dzienny wskaźnik nastrojów inwestorów przy użyciu analizy głównych składowych zmiennych rynkowych. Przeprowadzono badanie zachowania indeksu nastrojów inwestorów w okresie od stycznia 2019 r. do kwietnia 2020 r. i oceniono jego dokładność predykcyjną dla dziennych stóp zwrotu z akcji. Przeanalizowano również nietypowe zwroty i zmienność otaczającą badane zdarzenia przy użyciu metodyki analizy zdarzeń, modeli GARCH i testów nieparametrycznych. Wyniki wskazują, że nastroje inwestorów cechowały się odmiennymi wzorcami zmian w poszczególnych sektorach, z zsynchronizowanymi spadkami w okresie wokół szoku egzogenicznego. Badanie wykazało występowanie przyczynowości typu Grangera między ogólnym wskaźnikiem nastroju inwestorów a dziennymi zwrotami z akcji. Ponadto stwierdzono znaczne różnice w skumulowanych ponadnormatywnych zwrotach między przedsiębiorstwami o wysokich i niskich poziomach nastrojów inwestorów, zwłaszcza podczas

początkowego szoku, co sugeruje wpływ nastrojów inwestorów na zwroty z akcji. Nie zaobserwowano jednak analogicznego moderującego wpływu nastrojów inwestorów na zmienność cen akcji. Wyniki te sugerują, że choć nastroje inwestorów wpływają na wrażliwość cen akcji na nieoczekiwane szoki zewnętrzne, nie łagodzą jednak efektu zmienności. Badanie dostarcza praktycznych informacji na temat roli nastrojów inwestorów w okresach szoku zewnętrznego i podkreśla znaczenie miar nastrojów opartych na zmiennych rynkowych.

Słowa kluczowe*: nastroje inwestorów, czynniki egzogeniczne, finanse behawioralne, zmienność cen akcji, S&P 500*

ABSTRACT

The Role of Investor Sentiment in Moderating the Impact of Exogenous Shocks on Stock Prices

Lukas Udo Honecker

The research problem investigated in this thesis concerns **the role of investor sentiment in shaping stock prices during exogenous shocks**. In particular, the study **aims to deepen the understanding of the role of market-based company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices**. The exogenous shocks analyzed in this thesis are three significant events that occurred during the outbreak and initial spread of COVID-19 in 2020, which are (1) the announcement of the first confirmed positive COVID-19 case in the U.S., (2) the declaration of COVID-19 as a public health emergency in the U.S., and (3) the World Health Organization's official declaration of COVID-19 as a global pandemic. The research utilizes data from 367 US companies, constituents of the S&P 500, and constructs a daily investor sentiment indicator using principal component analysis of market variables. It analyzes the development of the investor sentiment indicator over the period from January 2019 to April 2020 and evaluates its predictive accuracy for daily stock returns. The study analyzes abnormal returns and volatility surrounding these events using event study methodology, GARCH modeling, and non-parametric tests. The findings indicate that IS exhibited varying movement patterns across different sectors, with synchronized downturns during the period of external shock. The study revealed Granger causality between the overall sentiment indicator (OSI) and daily stock returns. Additionally, significant differences in cumulative abnormal returns were found between high- and low-IS firms, especially during the initial shock, suggesting that IS influences stock return reactions. However, no corresponding moderating effect of IS on stock price volatility was observed. These results imply that while IS impacts stock prices' sensitivity to unexpected external shocks, it does not mitigate the effects of volatility. The study offers practical insights into the role of IS during periods of external shock and emphasizes the importance of market-based sentiment measures.

Keywords*: investor sentiment, exogenous shock, behavioral finance, stock market volatility, S&P 500*

ACKNOWLEDGMENTS

For Alisa & Jakob

As a strong believer in lifelong learning, writing my own dissertation has been my dream for many years, which would not have come true without the support of the University of Gdansk, my family, and the motivating words of my friends.

First of all, I would like to thank Dr hab. Anna Blajer-Gołębiewska, prof. UG, for the numerous exchanges, the time commitment, and the many positive advices in the past years, especially in the difficult phases of the project. Furthermore, I was lucky to have Dr Sabina Nowak by my side. I am grateful for her ever-patient support in setting up the research framework and developing the methodology for the dissertation. I am still impressed by her excellent eye even for small details in large spreadsheets.

Additionally, I would also like to thank my wife Alisa for her patience, understanding and encouragement, especially during the intensive work phases. Apart from that, my mother Elisabeth, my father Udo and my sister Hannah also deserve my gratitude - without your support and encouragement, I would not have been able to continue during the difficult phases and complete my dissertation.

A big thank you to all of you.

LIST OF PUBLICATIONS

Authors: Anna Blajer-Gołębiewska, Lukas Honecker, Sabina Nowak

Investor sentiment response to COVID-19 outbreak-related news: A sectoral analysis of US firms

published in The North American Journal of Economics and Finance ($IF_{5\text{-year}}$ = 3.7; IF_{2024}= 3.9), 2024, vol. 71, no. 102121, doi: 10.1016/j.najef.2024.102121.

PRESENTATIONS AT CONFERENCES

- Lukas Honecker, Sabina Nowak, Anna Blajer-Gołębiewska, *Investor sentiment response to Covid-19 pandemic-related news*, Sopot Conference on Modelling Contemporary Economies, Sopot, 30-31.05.2023, University of Gdansk
- Sabina Nowak, Lukas Honecker, Anna Blajer-Gołębiewska, *Investor sentiment at the outbreak of the pandemic / Nastroje investorów w obliczu pandemii*, Economic Challenges of the XXIst Century: Poland – European Union – World, Międzyzdroje 5-7.06.2023, University of Szczecin
- Sabina Nowak, Anna Blajer-Gołębiewska, Lukas Honecker, *The moderating effect of company-specific investor sentiment on stock price reactions to exogenous shocks,* 2nd Modern Finance Conference (MFC 2025), Warszawa, 7-9.09.2025, University of Warsaw

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

ATR Adjusted Turnover Rate

CAPM Capital Asset Pricing Model

DNSI Daily News Sentiment Index

DJIA Dow Jones Industrial Average

GICS Global Industry Classification System

LTV Logarithm of Trading Volume

OSI Overall Sentiment Indicator

PCA Principal Component Analysis

PLI Psychological Line Index

RSI Relative Strength Index

IS Investor Sentiment

S&P 500 Standard & Poor’s 500 Index

WHO World Health Organization

CHAPTER 1
INTRODUCTION

> "Psychology is probably the most important factor in the market – and one that is least understood."
>
> – David Dreman

Even though famous investor David Dreman's quote dates back to 1977, it is still largely valid today. Just like psychological factors expressed on the stock market through the beliefs, expectations, and, as a result, behaviors of investors were challenging to grasp back then, they remain so in many respects today. In particular, the connection between the increasingly observable, collectivist-irrational behavior of investors and the resulting market movements has attracted considerable attention in recent years (Marker, 2021), rendering the classic Expected Utility Theory, according to which only return and risk are price-forming factors, *ad absurdum* (Roßbach, 2021).

The reasons for the increased occurrence of collectivist-irrational behavior are manifold. Not only the significantly simplified access to the stock market via so-called "neo-brokers", some of which provide fast and easy access to the world's financial markets as an application on a smartphone to anybody in the world, the increase in algorithmic trading strategies but also the growing role of social media platforms, which enable a faster and less filtered transmission of emotions and sentiment by a wide variety of influencers at a subjectively ever-increasing speed (Li *et al.*, 2023), are important trends in the recent years. At the latest, with the "hype" surrounding the shares of video game retailer GameStop in 2020 (New York Times, 2021), in which numerous individual investors agreed on concerted short squeezes on the internet platform Reddit, forcing many short sales by institutional investors to be liquidated, it became clear that the topic of investing no longer only reaches a limited target group of informed investors but appeals to a broad, sometimes more and sometimes less informed "mass" of people. The term "dumb money", describing the title of a movie about the collective GameStop short squeeze (New York Times, 2023), shows that investing in the financial markets is no longer purely rational, but in some cases highly emotionalized. Increasing herd behavior without rationally discernible reasons, ignoring fundamental data in favor of rumors or trends, or rapid price movements without clear reasons are the symptoms of this development (Lyócsa *et al.*, 2022; Li *et al.*, 2023).

In addition to concerted actions, other situations make the influence of emotions on the financial markets particularly visible. An example is a so-called **exogenous shock situation**. These are **sudden, unexpected, exogenous events that were not anticipated by investors and players in the financial markets and, therefore, could not be priced in rationally and at an early stage** (Horn, 2022). Various events in the recent past, such as the outbreak and spread of COVID-19 starting in 2019 or the escalation of the war in Ukraine due to Russia's full-scale invasion in 2022, and their impact on global stock markets show that financial market players react excessively to such news in a short period (Figure 1), without there initially being a rational and obvious basis for this (McKinsey, 2021). It can be deduced from such situations that emotions play an (increasingly) important role in determining at least part of the impetus on the financial markets.

The emotional expectation of an investor, whether positive or negative, can be described with the generic term investor sentiment. Due to the increase in sentiment-driven behavior in the financial markets, a better understanding of how emotions arise and how they work, both in general and specifically when certain events occur, is essential today and in the future. Investors who want to operate successfully in the financial markets in the future must first understand factors influencing the emergence of positive or negative investor sentiment and, second, the role investor sentiment plays in stock price movements and the volatility of securities.

However, measuring investor sentiment remains a complex challenge. Many existing approaches have limitations, such as a lack of data quality, methodological weaknesses, or insufficient integration of psychological aspects.

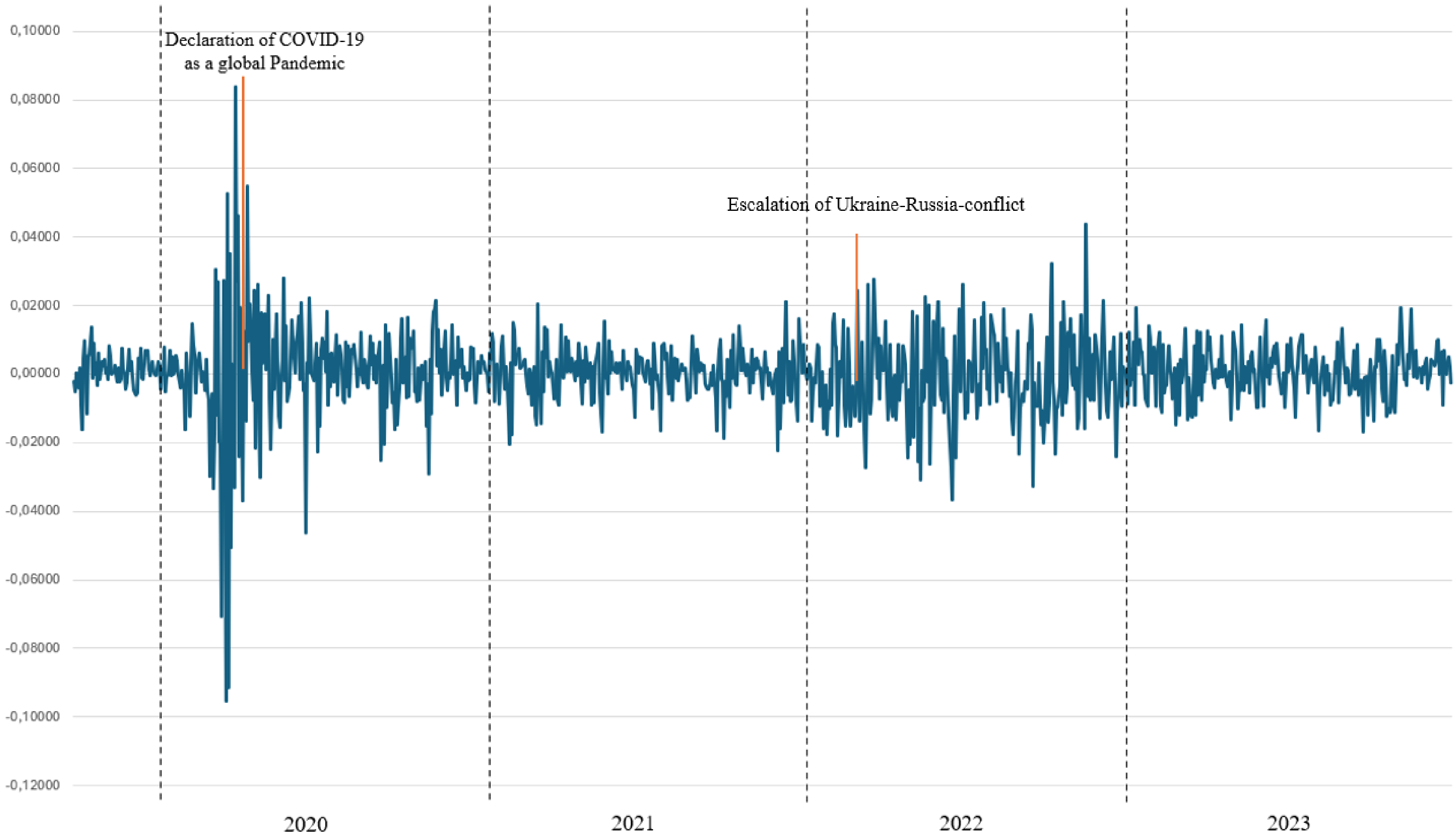

Figure 1. Daily Returns of MSCI All Country World Index 2020-2023

Source: own compilation based on https://www.msci.com/end-of-day-data-search.

This dissertation aims to identify these gaps, identify approaches to accurately measure investor sentiment, and add important new insights to the existing literature, particularly on the role of investor sentiment when exogenous shocks occur. By integrating modern financial theories and advanced statistical methods and considering multidimensional influences on investor sentiment, this dissertation seeks to address existing gaps in the current research literature and provide further research impulses for future studies. By focusing the study on the companies included in the S&P 500 index, it can be ensured that the results can be used as a basis for future research due to the broad availability of data and acceptance of the index as a research subject.

1.1 Motivation & Research Gap

The motivation for this dissertation are three relevant aspects that have not yet been sufficiently examined in previous research. First, a reliable operationalization of investor sentiment is still missing. The topic of investor sentiment has been represented in academia since the 1960s, at least in its first preliminary forms, such as "noise", as a field of research in the context of behavioral finance (although this term was not coined until a later date) (Black, 1986). While "classical" financial research, based on the rational behavior of *homo economicus*, predominantly deals with causally logical and thus rationally explainable behavior of financial market participants, behavioral finance increasingly pursues the measurement of irrational behavior (Roßbach, 2001). Measuring this irrational part of the behavior of financial market players, in contrast to the supposedly rational part determined according to "theory," is challenging and has not been clarified in science for a long time. Accordingly, numerous research approaches are circulating on the operationalizability and, thus, predictability of investor sentiment. Many studies have linked their approach to measuring investor sentiment with an attempt to prove a causal forecast relationship with the development of security or index prices. Indeed, if it can be proven beyond doubt that investor sentiment can be used to draw conclusions about future price trends, this would have a lasting effect on the behavior of "informed" financial market participants.

However, precisely this "unambiguous" operationalization poses challenges for academics. In particular, the multivariate factors that exist in reality and influence the further price development of a security make it difficult to operationalize. As will be shown in a later chapter, various research approaches have been developed that exhibit correspondingly different levels of predictive accuracy in different market situations. Even though investor sentiment is already the subject of intensive research, the question of a reliable operationalization of investor sentiment remains not entirely answered.

This dissertation is intended to contribute to the operationalization of investor sentiment. On the one hand, it tests the suitability of an already introduced sentiment indicator in a new context and, on the other hand, supplements it with a new proposal for the aggregated consideration of individual sentiment indicators.

Second, the role investor sentiment plays in investor decisions in the context of exogenous shocks, such as the COVID-19 outbreak, has not yet been fully uncovered. The role of investor sentiment in the occurrence of numerous and diverse exogenous shock situations has already been analyzed extensively using a wide variety of approaches. It has already been proven that emotions play a greater and more significant role than in “normal” times, especially when sudden, unexpected events occur (e.g., Sun & Shi, 2022). Of particular interest, especially in the case of exogenous shock situations, is the fact that the cause of the sentiment cannot be clearly explained yet. While more recent sentiment research increasingly distinguishes between emotional, sentiment-driven behavior and (supposedly) “irrational” behavior based on “rational” reasons such as a rational reaction to increased uncertainty or risk (Lee & Ryu, 2024), this distinction is hardly possible immediately after a shock situation, as investors react fast and immediately.

Even though the effect of investor sentiment in the wake of exogenous shocks has already been researched in general, such an analysis has not yet been sufficiently conducted for the outbreak and spread of COVID-19 in 2019 and the first half of 2020. So far, little is known about investor sentiment development during this period or the influence of investor sentiment development on the share prices of individual companies. In particular, little attention has been paid to the behavior of investor sentiment on a daily and company-specific level and the moderating effect of investor sentiment on the occurrence of abnormal returns following shock events in the wake of COVID-19. It could be that companies with a particularly positive sentiment, even during a negative, exogenous shock, subsequently suffer lower cumulative negative returns than comparable companies with an initially more negative sentiment. The question, therefore, arises as to whether investor sentiment has a “protective” effect on the security prices of companies after an exogenous shock situation, i.e., whether the direction or intensity of sentiment impacts the return of a stock. This dissertation seeks to address this research gap with an in-depth examination of the course and influence of investor sentiment during events related to COVID-19.

Third, the effect of events during the COVID-19 outbreak on individual companies' stock prices and stock price volatility has not yet been intensively investigated. Although studies indicate that the volatility of overall markets and broad indices increased, a more detailed analysis of individual companies in these markets has not yet been carried out. In many studies examining the effect of shocks on stock price volatility, stock price volatility itself is seen as a sign of uncertainty in the markets. It is, therefore, used as a sentiment indicator but not as a research object at the individual company level. In addition, the impact of significant events in the wake of COVID-19 on the stock prices of individual companies has not yet been sufficiently researched. The question of whether cumulative abnormal returns occurred in the course of the COVID-19 pandemic for individual companies has not been conclusively answered comprehensively. This dissertation will contribute to the growing literature by using a proven approach to measuring stock price volatility changes following unexpected events in the new context of COVID-19 and analyzing the occurrence of abnormal returns after different events in the context of COVID-19.

Better knowledge and broader insights into investor sentiment would have numerous implications for various target groups: Researchers will be enabled by the new findings to better understand the emergence, impact, and role of investor sentiment, especially during shock situations. For investors in the financial markets, more profound insights into rational and behavioral mechanisms have even more far-reaching implications. New insights into the change in investors' emotionally-driven behavior due to the effect of sentiment as a behavioral factor will enable them to increase the resilience of their portfolios by providing better protection against sudden shocks. In addition, this target group has the opportunity to make strategic investment decisions and portfolio allocations based on a better understanding of possible influencing behavioral factors and thus to make successful investment decisions even in years of economic losses (such as in 2020, when the global economic growth was -4.3% due to the outbreak of the COVID-19 pandemic (World Bank, 2020)). In particular, the impact of shock situations on stock prices and stock price volatility can impact the strategies of holders of derivative instruments, such as warrants in terms of risk management. However, it can also provide new approaches for short-term trading potential. Overall, knowledge of the mode of action and interaction of rational and emotional behavior increases. In addition, the dissertation contributes to the growing literature on COVID-19 and its implications. **Consequently, the research problem in this thesis is the role of investor sentiment in shaping stock prices during exogenous shocks.**

1.2 Research Aim and Research Questions

Derived from the research gaps as described in theoretical chapters and by employing a robust framework of scientific theories, methodologies, and insights from previous studies, the research problem will be investigated further. **The primary aim of the study is to deepen the understanding of the role of company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices.** This is done by analyzing company-specific sentiment measurement, impact on stock prices, and implications, with a special focus on behavior and impact during exogenous shocks. Several aspects contribute to achieving this primary goal. They are expressed in the following research questions.

The first aspect serves to deepen the understanding of the research problem in a systematic and structured way. To this end, it is first necessary to gain an overview of the theoretical foundations that form the basis for the further analysis of the research problem in order to determine the further research framework for investigating the other research questions and the further procedure with regard to the methodologies to be used.

Research Question 1 (RQ1): What are the theoretical foundations of the research problem?

Building on Research Question 1, the previous research literature also needs to be examined to establish the current state of knowledge. The main empirical findings need to be summarized as the basis for developing a further approach to the research problem. An understanding of the empirical findings from previous research makes a decisive contribution to shaping the research hypotheses and thus determining exactly which relationships should be investigated.

Research Question 2 (RQ2): What are the results of previous studies concerning the research problem?

The next aspect delves into the complex task of accurately measuring investor sentiment daily and on a company-specific level. It involves a thorough and detailed examination of how investor sentiment can be quantified, considering the complexity of company-specific factors.

The dissertation's ambition is to identify or confirm reliable methods and indicators that capture the nuances of sentiment within this context. Chapter 2.4; Chapter 4.2, and Chapter 4.3 will answer the research question, resulting in a suitable sentiment methodology framework derived from a detailed overview of existing approaches.

Research Question 3 (RQ3): What are the suitable methods of measuring investor sentiment on a daily and company-specific basis?

Another goal of the dissertation is to examine the validity of a selected market-based approach to measuring investor sentiment, particularly in forecasting stock prices' performance. This involves assessing whether investor sentiment, when measured through market indicators and aggregated from firm-specific sentiment data, can be a reliable predictor of how a market index will perform in the future. By doing so, the dissertation seeks to provide empirical evidence that could support or challenge existing market-based models. This research question will be answered in Chapter 6.2.

Research Question 4 (RQ4): Is investor sentiment measured using a market-based approach a reliable predictor of future security performance?

The next research question builds a bridge between the measurement of investor sentiment and the research aim. In order to analyze the role of investor sentiment in moderating the impact of exogenous shocks on stock prices, the choice of the correct research methodology is essential. The choice of a suitable research method is based on the theoretical foundation in combination with previous research approaches and findings.

Research Question 5 (RQ5): What is the most suitable IS calculation method for investigating the role of investor sentiment in moderating the impact of exogenous shocks on stock prices?

Another significant focus and goal of the dissertation is understanding the effects of exogenous shock events, such as the COVID-19 pandemic, on investor sentiment. The dissertation investigates how such unexpected events influence the development and the course of investor sentiment across different companies and sectors while analyzing the factors contributing to differences or similarities. In addition, the impact of exogenous shocks on the occurrence of cumulative abnormal returns and the development of the volatility of securities will be examined. At the same time, the question will be answered as to whether investors anticipated essential events during the COVID-19 outbreak or whether they led to a "shock" for investors and the stock markets. The goal is to uncover patterns and insights that inform future responses to similar crises. Research Question 5 is discussed in more detail in Chapter 4.2.

Research Question 6 (RQ6): How do exogenous shocks, like the COVID-19 pandemic, impact investor sentiment, stock prices, and stock price volatility across companies and sectors?

Research Question 6 deals with the concrete role of investor sentiment in stock prices' changes during the COVID-19 pandemic outbreak and its consequences for investor behavior. In particular, the question is to be answered as to whether high (low) sentiment immediately before the shock situation occurs has a positive (negative) influence on stock returns following the shock. The analysis wants to reveal whether sentiment plays a critical role in price fluctuations during these periods and how it might interact with other market forces. This research question will be answered in Chapters 6.1, 6.3, and 6.4.

Research Question 7 (RQ7): What is the role of investor sentiment in stock prices' changes during the COVID-19 pandemic outbreak?

Over the course of the outbreak and spread of COVID-19, new information unexpected by investors was released at various times. Strictly speaking, the COVID-19 pandemic is a concatenation of shock situations. Such a course of events has so far been insufficiently researched in the study of shock situations. The question arises about whether connections and effects can be identified when looking at the links between the shock situations.

This dissertation aims to shed light on the role and impact of investor sentiment through an isolated examination of individual events and to draw conclusions about interactions between exogenous shocks. This research question will be answered in Chapter 6.5.2.

Research Question 8 (RQ8): Are there any patterns in investor response to pandemic-related events?

The mentioned gaps in the current scientific analysis of investor sentiment are to be closed, on the one hand, by expanding the data sources to include daily, company-specific sentiment values and, on the other hand, by analyzing investor sentiment in greater depth at this level in the context of exogenous shock situations during the COVID-19 outbreak and spread. In addition, a sectoral weighting and summary of the companies under consideration allow conclusions to be drawn at this aggregated level about similarities and differences in the effects of investor sentiment in different sectors. These findings can be compared with the development of investor sentiment at the company-specific level. Research Question 8 will be answered in Chapters 6.1.3, 6.1.4, and 6.3.2.

Compared to many other scientific studies, this study adds value by calculating investor sentiment using a range of market-based indicators, rather than assuming it based solely on major price movements following unexpected events. This approach, which incorporates insights from behavioral finance and financial psychology, enhances transparency, comparability, and offers deeper insights into the factors influencing sentiment.

The research questions of this dissertation are summarized in Table 1.

Table 1. Summary of Research Questions

Research Questions	Chapters
RQ1: What are the theoretical foundations of the research problem?	2.1*; 2.2*; 2.3*; 2.4*
RQ2: What are the results of previous studies concerning the research problem?	2.3*; 2.4*; 2.5*; 2.6*
RQ3: What are the suitable methods of measuring investor sentiment on a daily and company-specific basis?	2.4*; 4.1*; 6.2.1*
RQ4: Is investor sentiment measured using a market-based approach a reliable predictor of future security performance?	3.1; 4.3*; 5.1.3; 6.2*
RQ5: What is the most suitable IS calculation method for investigating the role of investor sentiment in moderating the impact of exogenous shocks on stock prices?	4.2*
RQ6: How do exogenous shocks, like the COVID-19 pandemic, impact investor sentiment, stock prices, and stock price volatility across companies and sectors?	3.2; 3.3; 4.4; 4.5; 5.1; 5.2; 5.3; 6.1; 6.3*; 6.4*
RQ7: What is the role of investor sentiment in stock prices' changes during the COVID-19 pandemic outbreak?	3.4; 5.4*; 6.5*
RQ8: Are there any patterns in investor response to pandemic-related events?	6.1.3*; 6.1.4*; 6.3.2*

Notes: * Chapters directly answering RQ.

Source: own compilation.

By addressing these comprehensive research questions, the dissertation aspires to expand the theoretical understanding of investor sentiment and offer practical value to various stakeholders in the financial markets, including institutional and private investors, financial analysts, and policymakers. The ultimate goal is to contribute significantly to the field of behavioral finance by providing a deeper insight into the human elements of financial decision-making, thereby laying a foundation for further research in this area.

1.3 Structure of the Dissertation

The dissertation is divided into seven chapters: (1) Introduction, (2) Theoretical Foundation and Literature Review, (3) Hypotheses Development, (4) Methodological Foundations, (5) Research Design and Data Collection, (6) Investor Sentiment and Stock Prices during COVID-19 Outbreak: Empirical Study and (7) Conclusions and Limitations. The contents of the chapters build on each other and systematically work towards answering the research questions presented.

Chapter 1 explains the background of the dissertation. By explaining the gap in current research, and the motivation for this study, research questions to be answered in the investigation are derived. Based on the research questions, the general structure of the dissertation is described.

Chapter 2 provides an overview of the economic theories relevant to this dissertation. First, the concept of the “economic man”, which builds the foundation for almost any neoclassical economic model, will be briefly discussed. This is followed by a more detailed look at the concept of market efficiency as a foundation for modern finance theory. In contrast to the assumption of an equal distribution of information, the principal-agent theory, explained afterwards, describes the phenomena that occur when there is an unequal share of information between market participants. Then, a literature review of previous research on the impact of exogenous shocks on the financial markets is presented. The concept of investor sentiment is derived, the historical development of empirical research on the topic is examined, and the underlying assumptions and theories are discussed. In addition, previous developments and findings of behavioral finance on investor sentiment are presented and placed in relation to exogenous shock situations.

Chapter 3 derives the hypotheses for the empirical study from a synthesis of the previous scientific findings on investor sentiment and the research questions of this dissertation.

Chapter 4 provides a scientific and methodological overview of the econometric and statistical methods applied in this study. First, various types of sentiment indicators are discussed in detail. Then, based on the indicators' characteristics, advantages, and disadvantages, the sentiment indicator used for this study is selected. Subsequently, the construction of the chosen sentiment indicator, in which several econometric methods are used, is discussed in detail. The Granger test for causality, the event study, and the GARCH model methodologies are then described in more detail, and test procedures used for significance testing are discussed.

Chapter 5 describes the specific procedure for calculating the relevant data for further hypothesis testing. Based on the econometric methods described in Chapter 4 and the derivation of the specific methods to be used, Chapter 5 first describes how the sentiment indicator for the present study was calculated. Further details on the calculation of the final indicator show which calculation operations were necessary for which sequence. When selecting the test procedure, it is also shown which methods were initially used to check if the sample fulfills the necessary assumptions. The last two sections of Chapter 5 describe the methodology and specific calculation of the volatility analysis and the procedure for measuring the moderating effect of investor sentiment in the wake of exogenous shocks.

Chapter 6 presents the key results of the empirical analysis as part of the dissertation. The most important descriptive statistics of the aggregated and sectoral sentiment indicators are first described, providing an overview of their behavior. Then, the results of detecting the Granger causality between S&P 500 index returns and investor sentiment are described, the findings on the significance of the abnormal returns and abnormal volatilities are summarized, and, finally, the outcomes of the moderating role of IS during exogenous shocks are revealed. Based on these results, a reference to theoretically derived hypotheses is made. Furthermore, in Chapter 6, results are interpreted, discussed, and placed in the context of the COVID-19 pandemic. The last section deals with the most important implications of the results for further research into the effects of investor sentiment and with conclusions for private or institutional financial market investors. The final Chapter 7 summarizes the dissertation's results based on the research questions and points out the most critical limitations of the study.

This dissertation provides a substantial contribution to both theory and practice in the field of behavioral finance. It provides evidence on the behavior of investor sentiment and stock prices in response to exogenous shocks. The COVID-19 pandemic outbreak provided a unique opportunity to empirically analyze the behaviour of these variables during an exogenous shock in this natural experiment framework.

Furthermore, by empirically demonstrating how company-specific investor sentiment moderates the effects of exogenous shocks on stock price behavior and volatility, the study extends existing sentiment theories into an unprecedented empirical context. The research contributes theoretically by bridging the gap between sentiment-driven behavior and market reaction under crisis conditions, thereby refining the understanding of investor decisions within financial market dynamics.

CHAPTER 2
THEORETICAL FOUNDATION AND LITERATURE REVIEW

Chapter 2 outlines the theoretical foundation of this study, offering clear definitions of key elements and an in-depth exploration of the underlying concepts. Additionally, it provides information on how these theories are applied in research practice to date. In addition to the economic theories of *Homo Oeconomicus*, efficient markets, and the principal-agent theory, which are relevant to this study, a significant focus of Chapter 2 is on the topics of exogenous shocks, investor sentiment, and the COVID-19 pandemic, as the main pillars of the current dissertation. Lastly, the S&P 500 Index, as the basis for the sample in the current study, and the Global Industry Classification System, used in the study to analyze sector-related sentiment development, are characterized.

2.1 Concepts of Behavioral Finance in Contrast to Classic and Neoclassical Economic Theory

The scientific discipline of economics and finance is based on fundamental theories and assumptions about the behavior of market participants and markets. When looking at these phenomena in empirical terms and based on recent research, it becomes clear that such theoretical assumptions only have limited validity in reality. In the following section, the concept of the “economic man”, which builds the foundation for almost any neoclassical economic model, will be briefly characterized, followed by a more detailed look at the concepts of efficient markets and information efficiency as models of modern finance theory. In contrast to the assumption of an equal distribution of information, the principal-agent theory is outlined afterward, describing a concept of unequal distribution of information between market participants. In addition to these concepts, the area of behavioral finance, including the most critical assumptions and theories, will be summarized subsequently.

2.1.1. *Homo Oeconomicus*

The Economic Man or *Homo Oeconomicus* is one of the most essential concepts of neoclassical economic theory. Homo economicus is described as a “rational actor who always makes their decisions based on complete information and always tries to maximize own utility" (Kirchgässner, 2008). The foundations of the concept go back to 1776, when Adam Smith published his essay on "The Wealth of Nations", where he describes individuals being motivated by maximizing their utility, leading to a perfect resource allocation in a free market (Smith, 1776). Also, according to Bentham's concept of utilitarianism, released a few years later in 1789, maximizing pleasure and minimizing pain as the two "sovereign masters" of nature are the main drivers of human behavior (Bentham, 1789).

The concept of the *Homo Oeconomicus* or "economic man" itself has then more concretely been developed by John Stuart Mills in the late nineteenth century. However, he never used this term himself (Persky, 1995). Mills described people in simplified terms as human beings with four specific interests: accumulation of wealth, leisure, luxury, and procreation (Persky, 1995). The term "economic man" was first used by Ingram and Keynes in 1888 and 1890 (Persky, 1995), describing humans as "money-making animals" or as driven "solely by the desire for wealth" (Persky, 1995). Early on, therefore, the description of economic man was not only about maximizing individual utility but also very specifically about maximizing wealth - a postulate that can quickly be transferred to the securities market, which is the focus of the current study. Alfred Marshall (1890) and Vilfredo Pareto (1906) finally manifested the economic man by formalizing the principles and transferring them into concrete financial and mathematical models (Marshall, 2009).

As mentioned above, the neoclassical concept of *Homo Oeconomicus* is based on three characteristics: "rationality," "complete information," and "utility maximization".

Rationality of Market Participants

The principle of rationality is closely linked to the economic man model and a fundamental pillar of economic theory in general, particularly in the context of microeconomic decision theory. There are numerous definitions of the term rationality itself - also because the term can be used and discussed in different ways depending on the context in which it is used.

Gosepath (1992), for example, uses the term rationality to refer to behaviors, opinions, desires, etc. that are "well-founded". However, he points out that "well-founded" also requires a definition. He therefore distinguishes between formal and substantive concepts of rationality depending on whether the basis of the reasoning can also be (transculturally) rationally justified.

Herbert Simon distinguishes between rationality in the neoclassical-economic sense and rationality in cognitive psychology. Cognitive psychology assumes that a rationally acting individual makes a “reasonable” decision against the background of the available knowledge and context. In contrast, neoclassical economic theory equates a rational decision with utility maximization (Simon, 1986), taking into account the available information.

Consequently, the principle of rationality linked to the concept of *Homo Oeconomicus* states that individuals consistently and diligently incorporate all information that becomes known to them, including knowledge about the change of macroeconomic variables, changes lying within a company, and also the knowledge about alternatives into decision-making without a time lag and based on their individual preferences (Simon, 1972). According to Simon, theories on rationality can be divided into normative or descriptive concepts, depending on whether the aim is to describe a normative behavior derived from theory or whether the actual observed behavior of individuals, for example, is to be described. Furthermore, individual and organizational rationality can be distinguished (Simon, 1972).

In the context of this dissertation, the focus is on the rationality of individual market participants. Based on the theoretical concept, every new information about changes in macroeconomic variables can be measured in the resulting capital market prices, in theory, without a time lag. In this context, the rational behavior of market participants does not only incorporate the current situation of a company, but also, in particular, the (individual) assessment and expectation of the future situation of the company (Fama, 1970; Eden *et al.*, 2022). The editor of Börse Online, Hans G. Lindner, says that the stock exchange "as an investment market almost exclusively evaluates the future” (Wirtschaftslexikon24, 2020). This is the only way to explain a robust and momentum-driven movement of share prices as a result of supply and demand. If shareholders only ever evaluated the current situation of a company, large price jumps would only be conceivable in a few cases (Fama, 1970).

The Principle of Complete Information

The concept of complete information, which is often applied in game theory, assumes that individuals have all knowledge about their own preferences, options, and objectives as well as the same information for all other individuals, allowing them to set the best strategy to maximize their personal outcomes (Hunt & Zhuang, 2024). In other words, this means that on the one hand, individuals have all available information transparently available and, on the other hand, they fully incorporate this information into their decision-making process. Stigler (1961) already refers to the term "complete knowledge" when describing the theoretical situation that would help workers to find their perfect employment based on their individual preferences. However, due to "imperfect knowledge", in reality, this scenario is not applicable. Other essential works and studies, i.e., by von Neumann and Morgenstern (1944) on strategic interaction based on complete information (Von Neumann & Morgenstern, 2007), by Arrow (1963) on the role of information in economics (Arrow, 1996), by Akerlof (1970) on the implications of incomplete information for market mechanisms and market failure and Stiglitz (2002) on information asymmetries in markets, examined the concept of complete information. Their implications for the market participants and economic policy approaches to support market efficiency contributed to the concept of complete information in its empirical application, and found evidence that, in reality, incomplete information or asymmetric information distribution occurs in many cases. Derived from the fundamental postulate of complete information, various other concepts, i.e., the Efficient Market Hypothesis (EMH) or the Principal-Agent-Theory, were developed or concretized. Both concepts are central to the event study methodology applied in this dissertation, which is why the concepts are described in more detail in sections 2.1.2 and 2.1.3.

The Principle of Utility Maximization

Utility is a measure of satisfaction. As consumption increases, total utility rises but marginal utility decreases. So, the additional satisfaction derived from the next additional unit of a good is decreasing (Mankiw, 1998).

The principle of utility maximization states that an individual will always act in a way that maximizes their total utility (Kahneman & Thaler, 2006). With a given budget restriction, an individual will therefore always decide in such a way that the chosen combination of a set of goods with given prices returns the maximum utility (Samuelson, 1948).

The concept of the economic man stands in contrast to the occurrence of sentiment, as it postulates a strict formation of expectations based on fully transparently available information (Wang, 2001). It does not consider the fact that individuals can interpret information differently and, therefore, arrive at a different decision and, thus, different behavior even with identical availability of information. These differences may be expressed through factors such as personal risk tolerance, loss-bearing capacity, and behavior in uncertainty (Kahneman & Thaler, 2006). Similarly, sentiment plays a role in this information-processing process. This dissertation also seeks to further explore the impact of investor sentiment during specific market conditions.

2.1.2 Efficient Capital Markets & Information Efficiency

The concept of efficient capital markets is based on the principle of rationality, supplemented by considerations regarding the distribution of information on the capital markets between the supply and the demand side. Even though the first theories and concepts date back to the 16th century (Sewell, 2011), Fama's work on “efficient markets” in 1970 and two studies by Samuelson in 1965 and 1973 laid the foundation for the “efficient market hypothesis” (EMH), which is still valid today (Samuelson 1965; Fama, 1970; Samuelson 1973; Sewell, 2011). Up to this point, there were two prevailing theories on price formation in the (capital) markets. On the one hand, it was assumed that conclusions about future developments could be drawn by analyzing historical price trends. On the other hand, in contrast, the random walk theory stated that future price developments are random, independent of past price developments and inherently unpredictable (Fama, 1965).

The theoretical basis of Fama’s “efficient market hypothesis” is the assumption derived from the concept of rationality, share prices always reflect a company’s current (financial) state to create the basis for an efficient allocation of resources for all market participants. This enables companies to make investment decisions that maximize their benefits, while shareholders acquire shares at a price that takes all information about a company into account. “A market in which prices always ‘fully reflect’ available information is called ’efficient’” (Fama, 1970). In a case of an efficient market, ”even if all the available information were shared with all the market participants, the price of a security would remain unchanged” (Malkiel, 1992).

In conjunction with the random walk theory, it can be deduced from this postulate that all available information is already considered in current prices. Conversely, only new, future information is to be included during the stock price formation. From this, it can be deduced that even uninformed or poorly informed market participants with a broadly diversified portfolio can achieve an average market return (Malkiel, 1989).

In his article, Fama distinguishes between strong, semi-strong, and weak information efficiency (Fama, 1970). The foundation of this categorization already goes back to works from Roberts on the analysis of stock markets (Roberts, 1959; Roberts, 1967), but has been popularized by Fama (1970) (Williams, 1999). Weak information efficiency exists if only the data on historical price trends were equally transparently available to all market participants. In this case, an excess return from a technical analysis of the price trends would no longer be possible since the current prices already consider all the information from this analysis in their current amount (Fama, 1970; Held, 2004). Semi-strong information efficiency would exist if only all publicly available information on securities were equally available to all actors in the financial market (Fama, 1970). In this case, achieving an excess return from the analysis of fundamental data in addition to technical analysis would no longer be possible since all insights from fundamental data analysis have already been incorporated into the security price. Finally, strong information efficiency exists if all publicly available and private information (i.e., only known within a company; by internal stakeholders) becomes available to all market participants immediately after it arises (Fama, 1970).

If the concept of strong information efficiency were applicable in reality, the concept of investor sentiment would not be useful. In this case, all actors in the market would include all available information, i.e., all overt as well as covert information, in their decision-making and rationally adjust their expectations immediately (according to the principle of rationality). Investor sentiment is based on the assumption that irrational views and behaviors occur, making deviations in preferences possible. Strong information efficiency would still imply that all market participants would prefer individually chosen companies to other companies, but this preference would be exactly the same for all market participants. Consequently, an over- or under-return would no longer be possible; the return expected from the market corresponds to the equivalent of the investment risk. The concept of "investor sentiment" therefore assumes at most the occurrence of semi-strong information efficiency. The event study method can be used to test this form of information efficiency empirically (Fama, 1965; Fama, 1970).

In the meantime, numerous studies have examined the information efficiency of different markets and under different macroeconomic conditions (i.e., Kim & Shamsuddin, 2008, for different Asian markets; Abdmoulah, 2010, for the Arabian market). Realizing that the efficient market hypothesis can be empirically refuted under many conditions ultimately led to the emergence of behavioral finance (Sewell, 2011). Sewell concludes his review of previous studies on the EMH, stating that the EMH is "strictly speaking false" but "in spirit profoundly true" (Sewell, 2011). As such, EMH describes rather a theoretical situation which constitutes a reference point to analyze the extent of market inefficiencies.

In connection with the concept of information efficiency and the efficient market hypothesis, according to Fama (1970), Beaver (1981) introduced an adapted approach, considering a finer subdivision of the different types of information efficiency and taking into account different "beliefs" of the investors, which contribute to the formation of a so-called "intrinsic value" of a security. Beaver understands the intrinsic value as „the price of the security that would prevail if everyone else possessed the same endowments, preferences, and beliefs as that individual“ (Beaver, 1981), establishing a clear connection between the price of a security and sentiment (in this case, represented by the investor's "belief"). The role of "belief" and "perception" will be discussed in a separate section.

2.1.3 The Principal-Agent Theory

The principal-agent theory is an additional central concept in the economic analysis of asymmetric information relationships. It is often used to analyze incentive structures in the context of economic constellations. Based on the assumption of diverging interests on the one hand and unequal distribution of information between the company's internal stakeholders (agents) and shareholders (principals) on the other, the shareholder can only form their expectations regarding the future share price development on the information available to them. The correctness of the shareholder's assessment will always be associated with uncertainty due to the lack of insight into the company. The principal will thus incorporate this uncertainty to the same extent in the willingness to pay for the security. Higher perceived uncertainty of the company situation will thus lower the stock price. In contrast, the agent is interested in maximizing the stock price. In shareholder communication, there are, therefore, approaches to systematically reduce the perceived uncertainty on the principal side, i.e., by creating incentive systems or institutionalizing control mechanisms, e.g., through internal or external audits (Gompers, Ishii & Metrick, 2003). Furthermore, requirements issued by stock exchanges force companies' managers to publish specific information on their webpages, such as annual financial reports, current reports, ownership structure, analyst coverage, etc. (Blajer-Gołębiewska & Czerwonka, 2012).

Critical perspectives on principal-agent theory emphasize the simplifications and assumptions of the model (Moe, 1982), particularly about the rationality of the actors. However, the occurrence of the phenomenon is not disputed.

The concept of principal-agent theory is central to this study, mainly due to uncertainty on the shareholder side induced by the asymmetrical distribution of information. As explained, there is a significant correlation between uncertainty and the role of investor sentiment. Previous research has found a link between higher uncertainty due to asymmetric information and a more significant influence of investor sentiment on the pricing of shares (Brown *et al.*, 1988).

2.2. Behavioral Finance, Market Anomalies and Biases

Behavioral finance, as a subfield of behavioral economics, combines classic financial theory approaches with research theories from psychology or the social sciences, such as prospect theory, mental accounting, or loss aversion (Glaser *et al.*, 2003). Behavioral finance aims to provide a deeper understanding of market movements and participant behavior compared to traditional financial approaches (Glaser *et al.*, 2003). Typical objects of observation in this approach include behavior that is hard to explain under the classical rationality assumptions, such as overreactions, underreactions, herd behavior, and sentiment-based pricing. The concepts derived offer explanations for the often not purely rational actions of market players and the influence of emotional factors on decisions.

Events such as the Great Crash of 1929, Black Monday in 1987, or the "bursting of the dot-com bubble" at the beginning of the 2000s are today representative of large price movements that cannot be explained only by classical rational behavior. Especially when the information situation is non-transparent and unpredictable, the fluctuations seem to be subjectively more pronounced. Already John Maynard Keynes stated in 1936 that markets move under the subjective "animal spirit" of investors (Hicks, 1936). Classic financial market theory denies such “irrational” deviations from the expected securities prices, as it assumes that all market actors are rational or that rational actors dominate market events and that individual “irrational” actors, therefore, do not influence securities prices significantly.

The history of behavioral finance dates back to the early 1970s when researchers began to question the assumptions of traditional financial theory. At that time, scientists such as Amos Tversky and Daniel Kahneman began to incorporate psychological factors into economic decision-making to develop models that are “psychologically more realistic than those that came before” (Barberis, 2018).

Tversky and Kahneman (1979) developed the prospect theory as an alternative to classical utility theory, as it was derived from the concept of *homo oeconomicus*. Their essay "Prospect Theory: An Analysis of Decision Under Risk" (1979) describes a new approach to decision-making under risk and uncertainty (Kahnemann & Tversky, 2015), for which Kahnemann was ultimately awarded the Nobel Prize (Daxhammer & Facsar, 2017). On the one hand, the authors showed that people do not always act rationally and that decisions are based on the perceived potential for gains and losses; on the other hand, they combined these findings with research results from brain research that locate the formation of (financial) decisions in the cerebellum, which is responsible for the formation of emotions (Daxhammer & Facsar, 2017). This concept of prospect theory made it possible to explain phenomena such as loss aversion and overreactions to new information. Two years later, Shiller (1981) found that some price movements of securities cannot be explained only by (rational) predictions of future cash flows, while De Bondt and Thaler (1985), two pioneers of behavioral finance, proved that some behavioral biases (e.g. overreaction) can create opportunities for excess returns which are disproportionate to (higher than) the corresponding risk.

At the end of the 1980s, the so-called "noise" concept emerged, which attempted to explain price fluctuations that were not based on rational considerations, but much more on investors' attitudes towards the security in question or the market in general (Black, 1986). Black (1986) and DeLong *et al.* (1990) showed that share prices in certain situations deviate significantly from expected prices based on the fundamentals. In the 1980s, researchers extended the ideas of Tversky and Kahneman to the financial markets in an environment of growing interest in behavioral finance theories (Roßbach, 2001). Richard Thaler coined the term "mental accounting" to explain how people make financial decisions based on mental categories (Thaler, 1985). The publication of Thaler's book "Advances in Behavioral Finance" (first published in 1993) supported the further establishment of behavioral finance as an independent field of research (Thaler, 2005). Thaler investigated various behavioral anomalies and their effects on markets and investment decisions.

The so-called "bursting of the dotcom bubble" at the end of the 1990s and the beginning of the 2000s further increased interest in behavioral finance. Nobel Prize winner Robert Shiller coined the term "irrational exuberance" and argued that markets are often influenced by irrational beliefs and herd behavior (Shiller, 2015).

The global financial crisis of 2007-2009 and the failure of traditional models to explain the extreme market movements further underpinned the importance of behavioral finance (Barberis, 2013). The crisis ultimately increased interest in integrating behavioral finance into mainstream financial practice. Thus, in the aftermath of the financial crisis, behavioral finance developed with a more vital research focus on applying behavioral concepts in financial practice. Institutional investors and financial advisors use behavioral finance insights to understand emotional factors better and how they can influence markets.

Behavioral finance's attempts to develop models with greater realism from a psychological perspective can be summarized along three categories: belief, preferences, and cognitive limits (Barbaris, 2018). Firstly, models based on beliefs focus on the idea that individuals do not fully adapt their reactions based on rational considerations (leading to over- and underreactions, i.e., in rare events such as exogenous shocks) (Simon, 1955; Barbaris, 2018). Secondly, the research focusing on preferences investigates what drives people's perception of utility, with the mentioned prospect theory as the most famous representative (Barbaris, 2018). Lastly, assuming that individuals do not incorporate every information available immediately and in an entirely rational manner into their decision-making process forms a third research strand, "cognitive limits" (Barbaris, 2018).

Market Anomalies and Biases

Derived from the various approaches, several types of market anomalies have already been empirically proven. Market anomalies are phenomena that cannot be explained by the principle of rationality or the Efficient Market Hypothesis (Woo *et al.*, 2020) and which, therefore, suggest the occurrence of behavioral factors affecting investors' decisions. These include, for example, the value effect (Fama & French, 1992), the January effect (Rozeff & Kinney, 1976), and the momentum effect of Jegadeesh and Titman (1993). Furthermore, Woo *et al.* (2020) cited the winner-loser effect, the herd effect, and the ostrich effect, as well as the occurrence of "bubbles" in general as examples of frequently observed market anomalies, while Liu *et al.* described a "holiday effect" (Liu *et al.*, 2022; Liu *et al.* 2023). Such observable market anomalies occur in practically all markets. They arise due to different behavioral biases and heuristics that shape human behavior, leading to deviations from market efficiency and rational behavior (Hon et al, 2021). In a literature review on behavioral biases occurring in individual investment decisions, Badola *et al.* distinguished 24 different biases impacting those decisions (Badola *et al.*, 2023).

Various studies analyze the relationship between investor sentiment and market anomalies. During exogenous shocks, phenomena related to investors' emotions, such as fear, panic, or anger, play a significant role (Goodell *et al.*, 2023). In a recent literature review, Goodell *et al.* (2023) show that emotions play a role in investors' decision-making and behavior and are directly related to market anomalies. Kumar and Lee (2006) found that retail investors buy or sell stocks "in concert", while analysts' forecasts or macroeconomic developments cannot explain this behavior.

In another study, Tsuchiya (2021) examined investor behavior after different shock situations. The author found signs of herd behavior but also demonstrated anti-herding behavior for stock price forecasters. The term “herd behavior”, coined by Patel *et al.* (1991), describes that “people will do what others are doing rather than what is optimal, given their own information” (Woo *et al.*, 20202). According to Shiller (1995), investors showing signs of herd behavior “assume that the others have information that justifies their actions” (Shiller, 1995). In the course of the COVID-19 outbreak, the occurrence of herding behavior was demonstrated, i.e., for the European markets (Bouri *et al.*, 2021), India (Dhall & Singh, 2020), and China (Wu *et al.*, 2020).

2.3 Exogenous Shocks

The primary aim of the study is to deepen the understanding of the moderating role of company-specific investor sentiment during exogenous shocks**.** The term “exogenous shock” will first be defined and characterized in the following section. This section is followed by an overview of research findings into exogenous shock situations and their impact on the global securities markets.

2.3.1 Definition and Characteristics

The global economy is undisputedly influenced by incidents induced by the environment and life (Widmaier, Blyth & Seabrooke, 2007). This is why it is also undisputed that a pronounced ability to anticipate such incidents and their impact on, i.e., customer needs, can represent a decisive competitive advantage for companies (Kandampully & Duddy, 1999). Therefore, companies and individual participants in the financial markets go to great lengths to analyze and anticipate future developments, trends, and environmental factors to minimize their risk as far as possible or to seek growth opportunities (Noy & Nualsri, 2007). However, not every event can be anticipated. There are also sudden, unexpected incidents, so-called exogenous shocks. In economics, an exogenous shock can be defined as an unanticipated event of low likelihood that is of an external nature and which entails disruptive changes and with consequences that are potentially existence-threatening (Taleb, 2010) or, more formally, as a "change in parameters or exogenous variables in an economic model" caused by exogenous factors (Horn, 2022). This means that the respective event changes the framework conditions for at least some economic actors and sometimes even the entire “economic order” (Widmaier *et al.*, 2007).

The sudden change in variables or parameters of an economic model has consequences for investor behavior. According to the efficient market hypothesis, market participants will immediately rationally adjust their expectations to the changed situation. In reality, however, the reaction of market participants to exogenous shocks occurs in a variety of ways and at different speeds. At the same time, behavioral factors also seem to play a role, mainly due to their sudden occurrence and the uncertainty induced by the shock situation. According to Barberis (2018), investors overreact to news, especially in situations of unclear or incomplete information. The actors in the financial markets, whether private or institutional investors, will react in the truest sense of the word "shocked", leading to sometimes irrational, unpredictable, or exaggerated reactions (Brown *et al.*, 1988; Black, 1986; Shiller *et al.*, 1984). Since security prices consider investors' expectations of companies' future development, they adjust their expectations accordingly, even during sudden events.

2.3.2 Exogenous Shocks and Market Behavior

There is no doubt that stock markets react to significant events (Al-Awadhi *et al.*, 2020) and that exogenous shocks, generally, are linked to market uncertainty (Baker *et al.*, 2024). The existing literature has already dealt intensively with exogenous shocks, with a particular interest in terrorist attacks such as the terrorist attacks in New York City in September 2001, financial crisis such as the global financial crisis in 2007-2009, natural disasters such as hurricanes as well as epidemics (i.e., the Ebola epidemic in Africa) and pandemics (such as the COVID-19 pandemic). This chapter mainly focuses on the effects of exogenous shocks on equity markets, although exogenous shocks also have numerous other socio-economic implications.

Terrorist Attacks

For terrorist attacks, it has been shown that they cause abnormally strong negative returns in the affected countries (Chen & Siems, 2002; Chen & Siems, 2007; Papakyriakou *et al.*, 2019). This effect tends to be short-term and becomes smaller over time (Llussá & Tavares, 2007). In the short term, such unpredictable events cause emotional reactions such as fear and panic, leading to panic selling (Burch *et al.*, 2016), while investors are more rational about their expectations in the medium term. The media coverage of such events, i.e., the media communication of terrorist attacks in the form of disturbing images and videos, can further intensify these negative feelings (Slone, 2000; Pizarro *et al.*, 2007).

The terrorist attacks of September 11th, 2001, in particular, have been examined in greater depth in numerous studies – mainly because their impact is not only limited to political implications but also had a significant economic impact (Nikkinen *et al.*, 2008). The costs for New York City following the terrorist attacks amounted to a level of 33-36 billion USD (Bram *et al.*, 2002), while the adverse effects on the stock markets after the attacks were also severe (Nikkinen *et al.*, 2008). Not only has the market in the US, the country where the attack happened, been affected (Charles & Darné, 2006). Contagion effects have also been observed in many other markets in different developed or developing countries (Nikkinen *et al.*, 2008). In a study by Carter and Simkins (2004), the authors found that the effect was visible in country indices and had measurable implications at the sector level. Companies in the aviation sector, i.e., were heavily affected by the attacks in September 2001, with larger airlines recording more significant losses than smaller airlines (Carter & Simkins, 2004).

Financial Crisis

Even if financial crises usually emerge over a period and from a wide range of information and events, they nevertheless represent a shocking situation with a heavy impact on the global markets. The global financial crisis of 2007- 2009, in particular, has been the subject of numerous studies that confirm far-reaching effects on the global markets.

Edey (2009) calls the global financial crisis “one of the most significant economic shocks in the post-war period.” Bartram and Bodnar (2009) found that the financial crisis of 2007– 2009 negatively impacted country indices and industries. Furthermore, they found that developed markets, such as the US market, were more heavily affected than emerging markets, which was also confirmed by other studies (Berkmen *et al.*, 2012). Al-Rjoub and Azzam (2012) specifically investigated the impact of the financial crisis on the emerging market of Jordan, also confirming that the global financial crisis of 2007-2009, the Asian-Russian financial crisis of 1997 and 1998, the financial crisis of 2005, as well as other exogenous events, led to falling stock prices. In addition, a study by Ryu *et al.* (2019) found that investor sentiment significantly impacted stock returns during the financial crisis of 2008 and 2009 in the Korean market.

Supported by further studies (Wolf, 1998; Nikkinen *et al.*, 2008; Kotkatvuori-Örnberg *et al.*, 2013), there is evidence that besides the effects of the financial crisis on directly affected markets or companies some additional interdependencies or contagion effects occur between different countries or companies, i.e., the developments of stock prices influence each other or events in certain countries can influence stock prices in other countries.

Natural Disasters

Various studies have also identified the effects of natural disasters on the stock market, indicating that the direction of effects may vary depending on the company, sector, and business model (Lee & Chen, 2020). A literature review analyzing the impacts of biological, climatological, geophysical, hydrological, and meteorological disasters in 104 countries between 2001 and 2019 reported heterogeneous stock market responses depending on the type and location of the event, with climatological and biological disasters leading to the strongest impacts on financial markets (Pagnottono *et al.*, 2022).

There is clear evidence that hurricanes have a significant and (predominantly negative) impact on the valuation of companies. A 2017 study showed negative cumulative abnormal stock returns after hurricanes (Feria-Dominguez *et al.* 2017). A study of Caribbean stock markets in the aftermath of hurricanes and other tropical storms showed that the losses in company values exceeded the material damage caused by the storms (Robinson & Bangwayo-Skeete, 2016). For the insurance sector, which is often a subject of investigation after natural disasters due to the damages to be settled, Hein *et al.* (2004) found that Hurricane Floyd negatively affected listed companies. In contrast, Wang and Kutan (2013) reported significant losses in the valuation of US insurance companies. However, they documented gains in the securities prices of insurance companies listed in the Japanese market after natural disasters. They argue with the "gaining from loss hypothesis", where companies gain in value after a significant loss of wealth in society (Wang & Kutan, 2013). Liu *et al.* (2022) found that the impact of hurricanes as climate-change-related events depends on the carbon intensity of companies, with coal companies losing more value compared to other stocks with "greener" business models and renewable stocks even gaining in value following Hurricane Sandy.

In contrast to the short-term adverse effects, another study proved that an increasing frequency of natural disasters had a long-term positive effect on human capital allocation, total factor productivity, and economic growth. This finding was based on falling investments in physical capital in the event of more frequent natural disasters and the associated relative increase in investments in human capital, as well as an increased rate of updating the capital stock in combination with an intensified adoption of new technologies (Skidmore & Toya, 2002).

Epidemics and Pandemics

The effects of epidemics and pandemics have also been extensively studied in many dimensions. Due to the COVID-19 pandemic, this field of research, in particular, was further fueled by numerous studies. In earlier studies examining the outbreak of SARS in Asia, Ebola in Africa, or the Zika virus in South America, far-reaching analogies were found concerning the economic effects. The SARS epidemic in 2003 alone wiped out 3 trillion US dollars in GDP (deLisle, 2003), and the cost of fighting the epidemic amounted to 50 billion US dollars (Lee & McKibbin, 2004). After the outbreak of SARS, stock prices and sector indices (in the concrete case of the study, publicly traded hotel chains) fell very sharply in a short period (M. Chen *et al.*, 2007). The results of a study by Blendon *et al.* (2004) indicated that the outbreak of infectious diseases leads to panic-like reactions, which may explain the significant reactions in the securities market. Nevertheless, in 2008, more than five years after the outbreak of SARS, it could be stated that the actual slumps and economic effects were not as strong in reality as initially assumed by some studies (Keogh-Brown & Smith, 2008).

The impact of the Ebola epidemic on stock market returns in general has been proven (Ichev & Marinč, 2018). Furthermore, Del Guidice and Paltrinieri (2017) proved that Ebola significantly influenced fund flows on the securities markets between 2006 and 2015, leading to a (negative) change in the performance of 78 African-based funds investigated. Huber *et al.* (2018) estimated the total economic and socio-economic burden of Ebola to be more than USD 53 billion.

The economic impact of the Zika virus in South America is considered to be relatively low. Although negative returns were observed on the day after the outbreak in Brazil, prices recovered within a short period of time (Macciocchi *et al.*, 2016). For other countries, such as the United States, the economic impact was also estimated to be significantly less than the Ebola outbreak in Africa, for example, at 0.5-2 billion USD (Lee *et al.*, 2017).

In connection with the outbreak of COVID-19, it was observed and documented that the outbreak of the pandemic in the affected countries led to sharp falls in the stock markets as well as to upheavals in society (Al-Awadhi *et al.*, 2020; Liu *et al.*, 2020; Ashraf, 2020; Dowd *et al.*, 2020; Singh *et al.*, 2024). In Asia, prices initially fell more sharply than in other parts of the world (Liu *et al.*, 2020). Social researchers describe the COVID-19 pandemic as a burning glass (Miller, 2020) or catalyst (Musleh *et al.*, 2022) for already existing tendencies toward new business models in connection with the progressive digitalization of society. In this context, it is not surprising that companies in the "new economy", such as the technology and IT sector, seem less affected by the COVID-19 outbreak shock than those in traditional industries (He *et al.*, 2020).

Furthermore, Huo and Qiu (2020) studied the substantial distortions in the Chinese stock market after the announcement of the lockdown in China. They found that securities with a lower proportion of professional investors reacted more strongly hostile to the lockdown. In addition, the authors showed that for individual companies having positive CARs in the event window, companies with lower idiosyncratic volatility and higher book-to-market value tend to perform better than other companies after one month. Another study shows that the extreme reactions on the stock market compared to previous pandemics are also due to the protective measures implemented, such as restrictions on public life (Baker *et al.*, 2020).

The specific link between significant disease outbreaks, epidemics, or pandemics prior to the outbreak of COVID-19 and the volatility of security prices has been surprisingly little analyzed. The few studies on this topic have tended to identify an increase in volatility, which was more pronounced in small companies than in larger companies (Pendell & Cho, 2013). Mazur *et al.* (2021) already found that companies included in the S&P 1500 experienced an increase in volatility after March 11th, 2020, when the World Health Organization declared the global spread of the coronavirus as a pandemic and introduced the official name for the disease COVID-19.

To summarize, exogenous shocks are unexpected events that have far-reaching consequences for the economy in general and the stock markets. There are indications that these effects, especially in the case of the outbreak and spread of COVID-19, are influenced, at least to a certain extent, by the sentiment-driven behavior of investors. The primary aim of the study is thus to deepen the understanding of the moderating role of company-specific investor sentiment during exogenous shocks.

2.4 The Phenomenon of Investors' Sentiment

„The stock market is the story of cycles and of the human behavior that is responsible for overreactions in both directions" - Seth Klarman

The theory of efficient capital markets assumes that investors adjust their expectations rationally and without delay to the current information situation. In practice, however, situations that cannot be explained by the classical theory occur time and again. As research progressed, the term “behavioral finance” finally emerged as an independent field of economics research (Baker & Wurgler, 2007), systematically dealing with the behavioral factors influencing investors' decisions and financial markets. An essential aspect of this “irrational” behavior, derived from the concept of "noise" which has been explained in Chapter 2.2, is the term “investor sentiment” (De Long *et al.*, 1990), which has since been the research object of numerous studies. Baker and Wurgler define investor sentiment simply as an "investor's degree of optimism or pessimism regarding financial markets" (Baker & Wurgler, 2006). Beer and Zouaoui define investor sentiment as “a belief about future cash flows and investment risks that is not warranted by fundamentals” (Beer & Zouaoui, 2013). Lee *et al.* (2002) argue, in turn, that investor sentiment expresses a systematic risk, which is priced in the stock prices. In everyday stock market parlance, the "bull market" or "bear market" is often widely referred to as a cross-market and macroeconomic manifestation of investor sentiment. Investor sentiment is thus based on the aggregate “perceived” performance of a company, a market, or the economy as a whole.

However, investor sentiment is not necessarily synonymous with purely irrational behavior on the part of market participants. A study by Verma *et al.* (2008) assumes that investor sentiment can be divided into an (irrational) part of noise trading and a (rational) part of fundamental trading. By examining two indices (including the S&P 500 index), they proved this distinction to be valid with both components linking to the stock returns of the indices (Verma *et al.* 2008). Later, Chau *et al.* (2016) showed that sentiment-driven traders can act as (rational) contrarians, buying when markets are falling (and sentiment is low) and selling when markets are rising (and sentiment is high). This does not contradict the thesis that investor sentiment is the aggregated perceived performance of companies, as perception also consists of an objective/rational and a subjective/behavioral component.

2.4.1 Perception

As investor sentiment emerges from an aggregated perception of a company’s performance, a clear understanding of the term “perception” is crucial for the investor sentiment concept. The concept of perception is often discussed, especially in philosophy. The Cambridge Dictionary defines perception as "a belief or opinion, often held by many people and based on how things seem“ (Cambridge University Press, 2024). This short definition contains several implications that are important for this study:

1. Perception is based on an assumption, a belief, or an opinion. Tye established a connection between belief and perception in the 1990s (Tye, 1995). Ultimately, perception is determined by what individuals "believe". This "belief" arises from a combination of the available information and an evaluation by the individual. Perception can thus be a highly subjective concept that can be altered by new information or a change in evaluation. However, it also contains an objective part, as belief can also be built on (rather) objective facts.
2. According to the definition in the Cambridge Dictionary, perception is often characterized by an opinion shared by several people (Cambridge University Press, 2024). This, therefore, means that the construction of the perception of a company is not exclusively individual but also the result of interdependence with other individuals. This aligns with the findings of Blajer-Gołębiewska (2021), showing that in the case of for investors' decisions are significantly influenced by collective perceptions, not by individual perceptions (regarding corporate reputation).
3. As a consequence, investors' sentiment as a perception of a market or company's performance thus depends on what information individuals receive from other individuals, how they evaluate this information, and what behavior they derive from it. This decision about the derived behavior is, therefore, to a certain extent made subjectively and irrationally.

2.4.2 Investor's Sentiment and Market Behavior

Some research has explored the phenomenon of investor sentiment in more depth, especially in relation to the observed behavior of different markets. Several studies have shown that investor sentiment plays a role in shaping returns on developed and emerging securities markets in general (Brown & Cliff, 2004; Qiu & Welch, 2004; Lemmon & Portniaguina, 2006; Mangee, 2018; Seok *et al.* 2019a). Sentiment-driven traders trade when their sentiment is positive and when stock prices are overvalued, leading to a reduced impact of trades on stock prices and increasing liquidity (Baker & Stein, 2004). As a consequence, opportunities for arbitrage are limited, and the movement in stock prices becomes unpredictable, reducing the reliability of stock price forecasts (Barberis *et al.*, 1998). A broad-based study examining the role of investor sentiment on stock returns found a negative correlation at the global level, while heterogeneous results were found at a local market level. To explain the ambiguous results, the author cites the impact of differences in the culture and institutions of the countries studied (Wang *et al.*, 2021).

Further research confirms that cultural and country-specific factors exhibit relevant influence on the phenomenon of investor sentiment (Baker & Wurgler, 2006; Seok *et al.*, 2019b). Chang *et al.* (2011) note that country-specific factors such as the legal system and the availability and quality of information seem to play an essential role in explaining country-specific sentiment. In this context, Schmeling (2008) proved that sentiment plays a role in nine out of 18 countries examined. In this study, country-specific factors seem to affect both the occurrence and strength of sentiment. Canbaş and Kandır (2009) investigated the relationship and causality between investor sentiment and stock returns using Granger's test for causality in the Turkish market. They found that investor sentiment in emerging markets might exhibit a different impact than investor sentiment in developed markets and that stock returns significantly impacted investor sentiment. Phylaktis and Xia (2006) showed a sentiment shift from a country effect to an industry effect, leading to implications for portfolio allocation. In addition to the impact of sentiment on the regular securities market, previous research has also examined the impact of sentiment on the warrants market (Burghardt *et al.*, 2008; Glaser *et al.*, 2011), the currency market (Sibande *et al.*, 2023), the options market (Lemmon & Ni, 2008) and the futures market (Smales, 2014; Gao & Süss, 2015), finding connections between market movements and investor sentiment.

Generally, the prevailing investor sentiment in a specific market seems to have a more substantial influence in cases of companies that are more difficult to value (i.e., stocks with high volatility, a low market capitalization, companies with high growth, young securities, etc.) (Baker & Wurgler, 2006; Kumar & Lee, 2006; Corredor *et al.*, 2013). It is, therefore, reasonable to assume that behavioral factors become more significant, particularly in situations of greater uncertainty or in decision-making under risk. Several studies confirm that the influence of investor sentiment on stock prices appears to increase, particularly in situations of more severe uncertainty (Brown *et al.*, 1988; Seok *et al.*, 2024). In addition, the direct impact of investor sentiment on stock market volatility has also been investigated, revealing a negative relationship (Lee *et al.*, 2002; Shen *et al.*, 2022). Furthermore, Kumari & Mahakud (2015) found that investor sentiment can predict volatility.

In the same context, Brown *et al.* (1988) developed the Uncertain Information Hypothesis (UIH), describing investors who set the fundamental price of a security lower in situations of higher uncertainty than in comparable situations with less uncertainty. The Overreaction

Hypothesis, developed by Barberis, Shleifer, and Vishny (1998), states that investors tend to overreact to bad news, leading to more substantial adverse stock price movements, followed by a stock price reversal when investors rationally adapt their behavior again, with a price returning to the fundamental value of the stock. Individual traders (Barber *et al.*, 2014; Chung *et al.*, 2016), as well as inexperienced traders (Kim *et al.*, 2017), seem to be more susceptible to irrational behavior in general and investor sentiment in particular.

French (2018) shows that investor sentiment affects returns after positive (festive holidays, sport matches) or negative (bombings, natural disasters) events. Several authors proved that investor sentiment plays a role in securities movements before and after scheduled economic events such as earnings announcements (Livnat & Petrovits, 2011; Mian & Sankaraguruswamy, 2012; Seok *et al.*, 2019b) or macroeconomic news (Seok *et al.*, 2022). In particular, Seok *et al.* found that the reaction of stock prices can vary depending on whether the content of earnings announcements is congruent with investors' expectations (Seok *et al.*, 2019b).

Other environmental factors also appear to have an effect on security prices, at least indirectly, through investor sentiment. Various studies have concluded that, for example, daylight (Kamstra *et al.*, 2003), outdoor temperature (Cao & Wei, 2004), cloudy weather (Goetzmann *et al.*, 2015) and sunshine (Saunders Jr., 1993; Hirshleifer & Shumway, 2003) have an impact on investor sentiment and thus on share prices. Yuan *et al.* (2006) also found that the phases of the moon have a link to investor sentiment.

Some studies suggest that investor sentiment influences the risk-reward relationship, also known as the risk-reward trade-off. Assuming efficient markets and rational market participants, the risk-reward relationship assumes a relationship between the risk taken and the expected reward, conditional on the available information. In other words, investors expect compensation as a corresponding return for the risk they take by purchasing a security (Yu & Yuan, 2011). The "market price" of risk is thus determined by evaluating the expected upside gain and the downside loss potential (Breckenfelder & Tédongap, 2012). Higher volatility generally also implies a higher expected return (Guo & Whitelaw, 2006).

If investor sentiment influences this relationship, a moderating effect between the input variable (risk) and the output variable (reward) can be attributed to investor sentiment. Current research initially provides evidence that the relationship between return and volatility changes over time (Chou *et al.*, 1992; Guo *et al.*, 2014) and is dependent on various factors, whereby the perceived risk compensation of investors with its subjective component also plays a role (Wen *et al.*, 2014; He *et al.*, 2019). He *et al.* (2019) explicitly investigated the effect of investor sentiment on investors' risk appetite, determining fluctuations in phases of varying sentiment levels.

Yu and Yuan (2011), as well as Wu and Lee (2015), proved in their studies that the relationship between risk and reward depends on the sentiment of the market under consideration. Yu and Yuan (2011) found that the mean-variance tradeoff is stronger in markets with high prevailing sentiment, while Wu and Lee (2015) confirmed the positive risk-return relationship in bull markets for US stocks. Yu *et al.* (2014) and Piccoli *et al.* (2018) investigated the influence of individual sentiment on the risk-reward relationship in different emerging markets. They proved that the risk-reward relationship is shifted positively during low sentiment periods.

More recent studies analyzed the asymmetry of investor sentiment and the risk-reward relationship, whereby the studies identified actual differences between phases of high and low sentiment. He (2022) found that low sentiment following bad news has a stronger influence on the risk-reward relationship than good news. The same study also found that individual sentiment measures are more useful for investigating the influence on the risk-reward trade-off than market-wide measures. Seok *et al.* (2021) found similar results for intraday investor sentiment (Seok *et al.*, 2021). A similar asymmetric impact of investor sentiment was also shown for its ability to predict stock returns (Chung *et al.*, 2012).

2.5 Investor Sentiment and COVID-19 Pandemic

The following chapter describes two central aspects of the dissertation in a common context: investor sentiment and the COVID-19 pandemic. Section 2.4 has already defined the concept of investor sentiment in more detail and presented the current state of research. In the following section, this concept will be explained in more detail in the context of the COVID-19 outbreak. Before, COVID-19 and the outbreak of the pandemic in 2019/2020 will be outlined in general terms using the most important data and figures.

2.5.1 Outbreak and Spread of the COVID-19 Pandemic

The COVID-19 pandemic or COVID-19 crisis, which is believed to have started with the spread of the “novel coronavirus SARS-CoV-2” (previously 2019-nCoV) around the world from the city of Wuhan in the People's Republic of China at the end of 2019, (Sohrabi *et al.*, 2020) has had an immense impact not only on public health but also on global economic systems (Velavan & Meyer, 2020).

On January, 31^{th} 2020—following a first confirmed case in the United States as a first country outside Asia ten days earlier on January 21^{st} 2020—a global health emergency was declared by the US Department of Health and Human Services (HHS) (Velavan & Meyer, 2020). On March 11^{th}, 2020, the World Health Organization (WHO) declared the global spread of the coronavirus as a pandemic and introduced the new official name for the disease caused by the virus: COVID-19 (Just & Echaust, 2020).

The rapid worldwide increase in infection numbers from January 2020 led to drastic measures and responses by many governments, such as lockdowns, social distancing, and travel restrictions to curb the further spread of the virus (Baker *et al.*, 2020). The government measures led to an unprecedented economic standstill and a significant impact on the global economy, reducing workforce and production volumes in many sectors (Nicola *et al.*, 2020). In 2020, the global economy shrank by 4.35% (World Bank, 2020). The unemployment rate in the US rose to a historical record of 14.8% (Congressional Research Service, 2021).

The financial markets experienced a sharp downturn worldwide in March 2020. According to Mishkin and White (2003), a market decline of more than 20% can be seen as a "market crash". During March 2020, the Dow Jones Industrial Average Index (DJIA) plummeted more than 25% (Mazur *et al.*, 2021), while the S&P 500 Index lost more than 30% (Shehzad *et al.*, 2021). In addition to the DJIA and the S&P 500 Index examined in this dissertation, the MSCI World Index, the DAX40 Index, and other major indices recorded significant price losses (Pandey & Kumari, 2021; Figure 2 and Table 2), presumably as investors sold *en masse* due to negative sentiment and panic-like, irrational behavior.

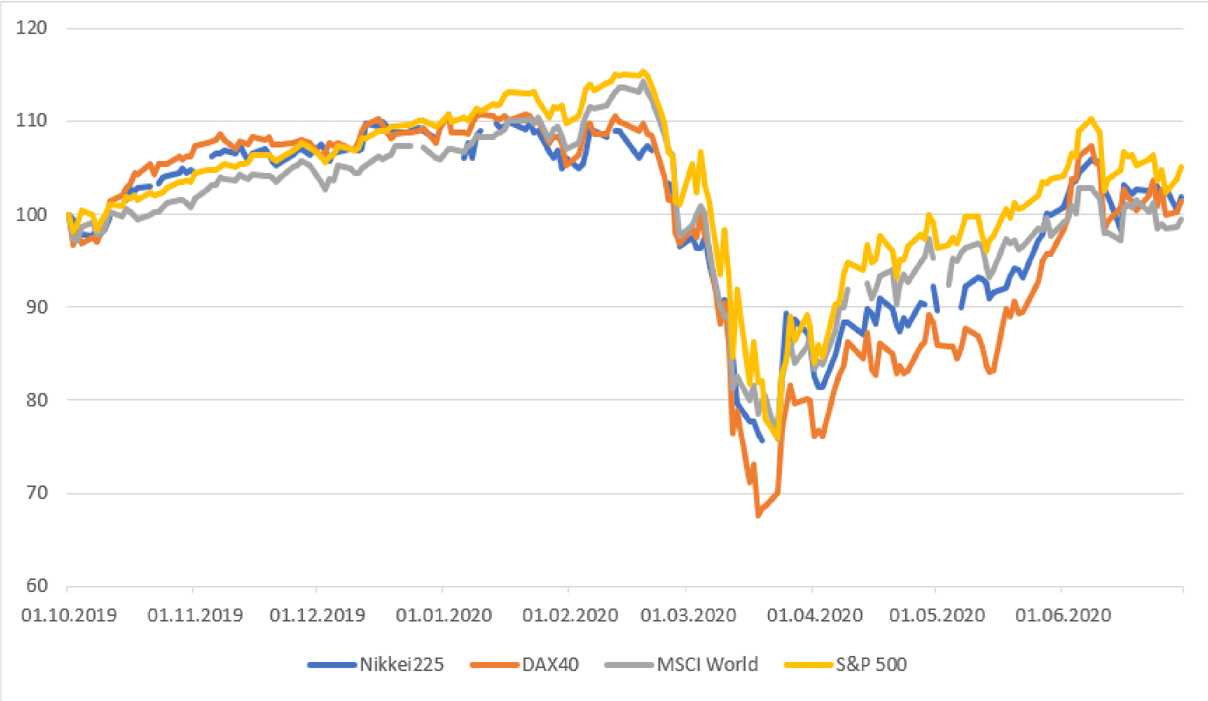

Figure 2. Development of Major Stock Indices between October 2019 and June 2020

Source: own compilation based on data from https://finance.yahoo.com/.

To cushion the economic impact of the pandemic, many countries subsequently introduced extensive economic stimulus programs and measures via their central banks, following a "whatever it takes" approach (Nicola *et al.*, 2020). For example, European countries committed to a 1.7 billion Euro rescue program (Nicola *et al.*, 2020). The measures ranged from direct payments to citizens to financial support for companies to maintain liquidity and protect jobs.

Table 2. Performance of Selected Stock Indices, March 2020 and Full Year 2020

Stock- / Market Index	Δ March 2020	Δ Full Year 2020
S&P 500 (US)	-12.5%	+16.3%
Nikkei 225 (Japan)	-10.5%	+16.0%
DAX 40 (Germany)	-16.4%	+3.5%
MSCI World	-13.2%	+14.1%

Source: own compilation based on data from www.statista.com.

As the enormous price losses in March 2020 opened up enormous price potential and thus offered an attractive entry opportunity for many new investors, while now being stipulated by intense support and rescue funds, the number of global private investors on the financial markets increased significantly. In Germany, individual (retail) investors increased by over 20% to 12.4 million (Deutsches Aktieninstitut, 2021). The simplified access options further strengthened this trend via smartphone apps and the growing availability of exchange-traded funds (ETFs), representing low-threshold, low-cost, and broadly diversified investment options for many investors. Consequently, the number of individual investors younger than 30 in Germany rose by over 65% (Deutsches Aktieninstitut, 2021). For the United States, the total number of individual investors more than doubled between 2019 and 2021 (JPMorgan Chase, 2023). However, with a growing number of individuals and comparatively uninformed investors, the susceptibility of securities prices to irrational behavior, such as herd behavior, FOMO (Fear of Missing Out), or panic buying, is also increasing (Kim *et al.*, 2017).

By the end of 2023, around 744 million confirmed cases of infection and seven million deaths were counted worldwide (WHO, 2024), making the COVID-19 pandemic the most significant "health emergency" ever recorded by the World Health Organization (BBC, 2020).

2.5.2 Investor Sentiment Behavior During the Outbreak of the COVID-19 Pandemic

A vast number of studies suggest that investor sentiment influenced changes in securities prices on the global markets during the outbreak of the COVID-19 pandemic. Although many aspects of the pandemic have been covered, less research has been conducted into how investor sentiment itself, i.e., the attitude of market participants towards individual companies, behaved throughout the pandemic.

Several studies found that the socio-economic or geopolitical uncertainty induced by the pandemic impacted investor sentiment (Haroon & Rivzi, 2020; Shaikh, 2021; Snarska *et al.*, 2025). In a study using the Google Search intensity index based on the Financial and Economic Attitudes Revealed by Search index (FEARS index) of the COVID-19 pandemic, a negative correlation between the COVID-19 pandemic and investor sentiment was identified (Dash & Maitra, 2022).

In addition, a study of US stock-listed companies found sector-dependent differences in the development of investor sentiment (Blajer-Gołębiewska, Honecker & Nowak, 2024), while another study for the Chinese market found a significant positive increase in investor sentiment among pharmaceutical companies compared to non-pharmaceutical companies (Song, Hao & Lu, 2021). Apart from that, Mili *et al.* (2024) proved the sensitive reaction of the investor sentiment proxies “Daily Trading Volume in the Market Index”, “Difference between High and Low-price Market Index”, “Psychological Line Index” and “Relative Strength Index” for Bahraini companies to news on COVID-19, with negative news having a more substantial effect on investor sentiment than positive news. This is in line with a study by Shaikh (2021), who also found a reaction of investor sentiment to the number of infected persons or deaths.

The effect of investor sentiment in the wake of the COVID-19 pandemic has also been examined in numerous studies (Sun *et al.*, 2021; Anastasiou *et al.*, 2022; Cevik *et al.*, 2022; Dash & Maitra, 2022), with fear in particular appearing to be a relevant factor. Haroon and Rivzi, i.e., found that their Coronavirus Panic Index (measuring the frequency of the words "panic" or "fear" in COVID-19-related news) shows a positive correlation with volatility in sectors affected by lockdowns during the fight against COVID-19 (Haroon & Rivzi, 2020). Salisu *et al.* (2020) also proved with their Fear Index, consisting of the factors "number of cases of infection" and "number of deaths", that fear in this operationalization is related to stock returns. This aligns with the findings of Donadelli *et al.* (2017), who already established a correlation between their Fear Index and stock returns in 2017. In the same study, a positive correlation between disease-related news (published by the WHO) and returns of pharmaceutical companies was demonstrated, which was also confirmed in a study by Sun *et al.* in the case of COVID-19 (Sun *et al.* 2021). The effect of fear on market volatility during the COVID-19 pandemic was also demonstrated by Li *et al.* (2022).

For the Chinese market, Sun and Shi (2022) showed, using an event study, that the trading volume immediately after the lockdown in the Chinese city of Wuhan started to increase more significantly for securities listed in Hubei (the higher-level province of Wuhan) than for stocks listed in other provinces. Similar effects were observed for airline securities (Martins & Cro, 2022; Maneenop & Kotcharin, 2020).

The research on COVID-19 is subject to constant evolution and a rapidly increasing number of studies. Initially, studies indicated that the COVID-19 outbreak impacted investor sentiment development for markets, sectors, and companies. In turn, investor sentiment also impacted the returns of the affected markets, sectors, and companies. At the time of writing this dissertation, the WHO has officially declared both the COVID-19 global health emergency and the pandemic itself to be over (United Nations, 2023). However, a particular focus of the dissertation is on the investigation of the period before and immediately after the pandemic outbreak.

2.6 The Standard & Poor's 500 Index and COVID-19 Pandemic

Section 2.6 begins by describing the S&P 500 Index, its history, the underlying inclusion criteria, and its significance for global investors, analysts, and researchers. The second part of the chapter takes a closer look at the reaction and performance of the S&P 500 Index during the COVID-19 outbreak.

2.6.1 The Standard & Poor's 500 Index

The Standard & Poor's 500 index, usually abbreviated as the S&P 500 index, has become an indispensable indicator of the US economy over the years. As a market index consisting of 500 selected shares of major US companies, it not only represents the health and stability of the US stock market but also provides insights into the overall economic health of the US as an economy (Capital, 2024).

The roots of the S&P 500 index go back to the 1920s, when the Standard Statistics Company (later Standard & Poor's) began compiling various stock indices. The first predecessor of the S&P 500 index, the S&P 90 index, was first issued in 1923 and initially comprised 90 stocks (Capital, 2024). The US economy developed rapidly in the following decades, making the need for a more comprehensive index increasingly clear. In 1957, the S&P 500 index was finally introduced, comprising 500 leading companies headquartered in the US and thus covering a broader and more representative range of industries (Capital, 2024).

The composition of the S&P 500 index is based on precise methods and quantitative selection criteria. To be included in the index, companies must meet specific criteria in terms of market capitalization (the company needs to qualify as a large-cap stock), liquidity, financial stability, and the percentage of shares available for public trading (S&P Global, 2024). This careful selection aims to provide a meaningful cross-section of the US economy with its various sectors and industries and to ensure the stability of the index.

Over time, the S&P 500 index has developed into a reliable indicator of the overall economic performance of the US, representing around 80% of the market capitalization (S&P Global, 2024). As a broadly diversified index, it not only reflects the development of the stock market but also proxies selected macroeconomic trends (Capital, 2024). Thus, analysts and economists use the S&P 500 index as a reference point to assess the state of the US economy. In addition, the S&P 500 index is used by investors globally as a reference for their investment decisions. The index's reactions to political events, economic indicators, and global developments directly impact trading strategies and portfolio allocations.

Understanding the historical performance and characteristics of the S&P 500 index is crucial for investors who want to diversify their portfolios and optimize their investment strategies and for researchers using the S&P 500 index to gain insights into (financial) economic phenomena. Due to its breadth and the predominant global market position and market capitalization of the companies included in the index, the S&P 500 index is one of the most frequently used reference large-cap indices in financial market research. In this dissertation, the S&P 500 index was chosen as the basis for the research sample for three reasons:

- The US is a developed industrialized nation with a largely stable political system and substantial financial reserves. These factors could influence investment decisions during the COVID-19 pandemic, so instabilities in these factors should be ruled out as far as possible.
- The fundamental data of the companies included in the S&P 500 index and information on corporate decisions are transparent and freely available due to the requirements of the US financial market authority (SEC, 2024).
- The 500 companies in the S&P 500 index represent a broad sample from the outset. As this investigation not only examines investor sentiment on an individual company basis and its effect on securities indicators but also summarizes and weights the companies by sector based on market capitalization, a sizable overall sample is necessary.

2.6.1 S&P 500 Index during the Outbreak of COVID-19

This section will briefly overview the most important findings on the relationship between COVID-19 and the S&P 500 index. The most relevant aspects will be discussed in more detail in the next chapters of this dissertation.

Many studies have focused on the impact of COVID-19 on the development or returns of major global indices, often including the S&P 500 index as a broad and relevant stock index (Ashraf, 2020; Al-Awadhi *et al.*, 2020). The S&P 500 index reacted sensitively to the outbreak and further development of COVID-19 in early 2020. In the first weeks after the outbreak of COVID-19 in the US, the S&P 500 index showed negative returns of up to 30% (Shehzad *et al.*, 2020). Figure 3 shows the daily returns of the S&P 500 index between January 2nd, 2019, and April 30th, 2020, visually confirming the sensitive reaction of the S&P 500 index to the COVID-19 outbreak.

In this context, a study by Yilmazkuday (2023) showed that the number of confirmed positive COVID-19 cases is related to a reduction in the S&P 500 index, with the strongest connection in March 2020. According to the author, a cumulative increase of 1% in case numbers led to a cumulative 0.03% reduction of the S&P 500 index after one week.

A study by Baker *et al.* (2020) concluded that in no previous pandemic, the US stock market reacted as strongly as in the case of the COVID-19 outbreak. The authors explain this strong reaction with the government interventions, such as the lockdowns introduced, which can potentially cause severe economic cuts in a service economy. This aligns with the findings by Ashraf (2020), who confirmed that government interventions led to negative stock market returns in different countries.

Sharif *et al.* (2020) analyzed the impact of COVID-19 on the US economy, the US geopolitical risk, and the economic uncertainty. The authors found that the outbreak had an even more significant effect on geopolitical risk and economic uncertainty than on the US stock market itself. Furthermore, Koçak *et al.* (2022) found that, despite the sizeable overall downturn of the index, companies in the S&P 500 index with low(er) carbon emissions (called "green companies" by the authors) even profited from the COVID-19 outbreak. This aligns with the results of Albuquerque *et al.* (2020), confirming that US companies with higher environmental and social (ES) ratings had significantly higher returns, lower volatility, and higher operating margins in the first quarter of 2020. Khalfaoui *et al.* (2021) found that the release of COVID-19 vaccines and the start of the vaccination campaign positively impacted the S&P 500 index returns.

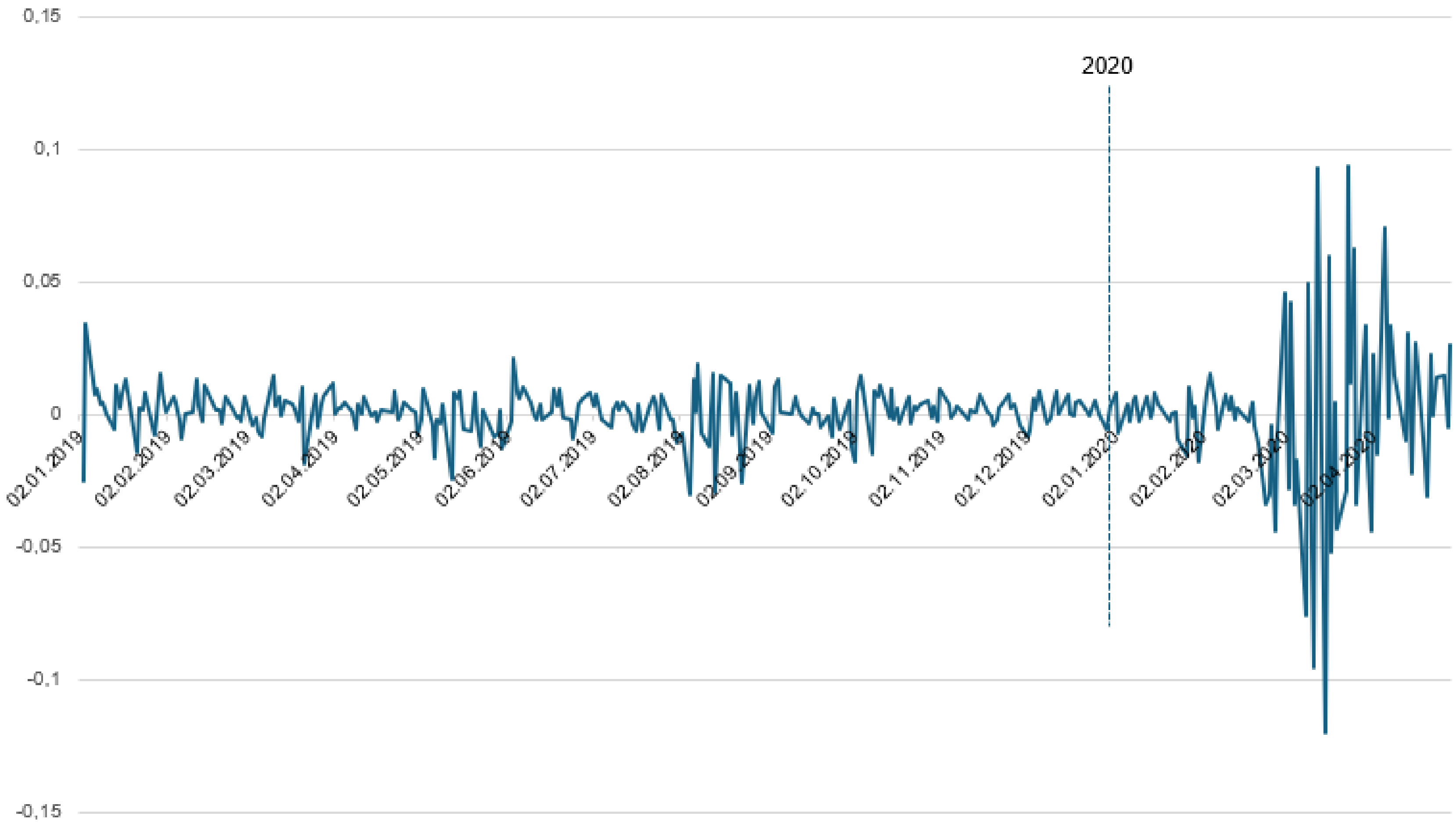

Figure 3. Daily Returns of the S&P 500 Index

Source: own compilation based on Yahoo Finance (2024).

2.7 Global Industry Classification System

In an economy characterized by increasing globalization and diversification, the possibility of applying a uniform structure to the business world, including a structured and uniform approach to classifying companies, is essential. The Global Industry Classification System (GICS) is a widely used system for classifying companies and assigning their business activities to sectors. The main objectives of the GICS are to facilitate comparisons between companies and sectors, improve the comparability of financial data, and provide a consistent basis for analyzing equity markets. The standardized classification enables investors and analysts to develop strategies, manage risks, and make investment decisions more effectively. Furthermore, it also enables a systematic framework for investigating economic issues to be established in the context of scientific research design.

The Global Industry Classification System was developed jointly by the international financial services companies MSCI (Morgan Stanley Capital International) and S&P Dow Jones Indices (MSCI, 2023). It was introduced in 1999 in response to the growing need to provide a standardized and consistent classification of companies for investors, analysts, and other financial players (MSCI, 2023).

The GICS divides the economy into a four-level hierarchy: Sectors consisting of one or several industry groups, which in turn consist of various industries, which are divided into different sub-industries. At the top level, there are eleven sectors, representing a wide range of economic activities, such as Information Technology, Healthcare, and Financial Services. Each sector is further divided into industry groups to provide a more detailed description of business activities (Table 3).

The 25 industry groups are composed of 74 industries, which can be divided into 163 sub-industries (MSCI, 2023). In 2023, the Global Industry Classification System was revised to align the (sub)industries more closely with the business activities of the classified companies (MSCI, 2023). As this dissertation only uses the first tier of eleven “sectors,” the structural changes did not affect the research framework.

Table 3. GICS Sectors and Industry Groups

Sector	Industry Group
Energy	Energy
Materials	Materials
Industrials	Capital Goods
	Commercial & Professional Services
	Transportation
Consumer Discretionary	Automobiles & Components
	Consumer Durables & Apparel
	Consumer Services
	Consumer Discretionary Distribution & Retail (new name after reclassification)
Consumer Staples	Consumer Staples Distribution & Retail (new name after reclassification)
	Food, Beverage & Tobacco
	Household & Personal Products
Health Care	Health Care Equipment & Services
	Pharmaceuticals, Biotechnology & Life Sciences
Financials	Banks
	Financial Services (new name after reclassification)
	Insurance
Information Technology	Software & Services
	Technology Hardware & Equipment
	Semiconductors & Semiconductor Equipment
Communication Services	Telecommunication Services
	Media & Entertainment
Utilities	Utilities
Real Estate	Equity Real Estate Investment Trusts (REITs) (new name after reclassification)
	Real Estate Management & Development (new after reclassification)

Source: MSCI, 2023.

Chapter 2 serves as the foundation for this study. Building on the research motivation and the research gaps, it presents the most important fundamental theories and concepts that form the basis for deriving the hypotheses in the next step of this research. The data and previous research findings on investor sentiment, COVID-19, and the S&P 500 Index presented in Chapter 2 help to embed the hypotheses in the right research context, paving the way for the empirical investigation undertaken in this dissertation.

CHAPTER 3
HYPOTHESES DEVELOPMENT

Knowing that investors' sentiment shapes the behavior of market participants and impacts stock prices, it is reasonable to posit that it could also contribute to the sudden occurrence of an exogenous shock. The primary aim of the study is to deepen the understanding of the role of company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices. This dissertation adopts a sequential approach, systematically addressing the research questions at subsequent stages. The first stage of the dissertation initially deals with a suitable and methodologically reliable determination of company-specific and sector-specific investor sentiment indicators, which form an important basis for the following stages. As part of the first stage, the Overall Sentiment Indicator (OSI) is also calculated, and its suitability for predicting the daily returns of the S&P 500 Index is examined.

The second stage of the dissertation examines the influence of the analyzed events on stock prices. The investigation is carried out by determining the CARs. Stage 3 examines the influence of the defined events on stock price volatility in more detail. Finally, Stage 4 examines the (moderating) role of investor sentiment in the formation of CARs before, during, and after the events examined in more detail. Chapter 3 derives the hypotheses for the empirical study from a synthesis of the previous scientific findings on investor sentiment (Chapter 2) and the research questions of this dissertation (Chapter 1.2).

3.1 Predictive Accuracy of the Overall Sentiment Indicator for Daily Stock Returns

As described in the introduction, the proof of a causal relationship, i.e., a connection between two variables in which changes in one variable (the sentiment indicator) directly result in changes in the other variable (e.g., stock price or stock volatility), constitutes a central objective in sentiment research. Accordingly, many researchers have investigated this relationship using different approaches (Fisher & Statman, 2000; Brown & Cliff, 2005; Kumar & Lee, 2006; Joseph *et al.*, 2011; Kim *et al.*, 2022). Even if a relationship between investor sentiment and stock returns has already been proven, it is not always possible to prove a causal relationship between sentiment values determined based on a theoretical methodology and stock returns, as timing and magnitude of the effect of investor sentiment on stock returns seem to be highly irregular (Frydman *et al.*, 2021). A study by Kim *et al.* (2022) suggests that sentiment indicators using market indices have a higher predictive accuracy for stock returns than news sentiment. Baker and Wurgler, whose index-based approach to sentiment measurement is one of the most widely used foundations for sentiment research today, “predicted” the future development of shares and their returns (Baker & Wurgler, 2007) using a market-wide approach. On the individual company level, the daily, company-specific sentiment indicator (OSI) by Seok *et al.* (2019a), which is based on the calculation methodology of Baker and Wurgler but includes other variables, has also already been tested for its predictive accuracy. In a 2019 study, Seok *et al.* (2019a) show that the level of firm-specific sentiment impacts the stock returns of the following day. In turn, Allen *et al.* (2019) proved that sentiment extracted from newspapers also predicts daily stock returns. In 2024, Seok *et al.* found that investor sentiment exhibits a more significant influence in situations of higher uncertainty (Seok *et al.*, 2024).

While the predictive accuracy of sentiment indices has been proven at both market-wide and individual company levels, the use of a firm-specific indicator at an aggregate level for predicting the returns of a market index has not been investigated in depth. Individual traders (Barber *et al.*, 2014; Chung *et al.*, 2016) and inexperienced traders (Kim *et al.*, 2017) seem more susceptible to behaviors beyond the neoclassical concept of rationality in general and investor sentiment in particular. At the same time, there is evidence that the sentiment of individual investors is more strongly expressed at a firm level (Hsieh *et al.* 2020). DeVault *et al.* (2019) argue that institutional investors drive market-wide sentiment to a large extent. By focusing on individual companies instead of market indices, capturing sentiment reactions by sentiment-sensitive retail investors following the COVID-19 events should become more accessible. This procedure aligns with Barber *et al.* (2017), who analyzed individual stock trades to investigate retail trading behavior. Based on these findings, it can be assumed that investor sentiment’s role is more pronounced at the firm level than at the market-wide level.

The performance of broad market indices, such as the S&P 500 Index, is determined by the performance of the companies included in the index. Companies and their influence on the overall index are weighted depending on various characteristics, such as market capitalization in the case of the S&P 500 Index. Suppose a company-specific sentiment indicator can reliably predict the stock returns of the companies under consideration. In that case, this should also be possible for predicting the market index returns if the sentiment aggregation is carried out similarly to forming the market index. Accordingly, the following hypothesis is proposed (Predictive Hypothesis):

H1: The Overall Sentiment Indicator is capable of predicting the daily returns of the S&P 500 index.

3.2 General Effect of Information about COVID-19 on Stock Prices

As comprehensively described in Chapter 2.5, the COVID-19 outbreak represents an external shock situation of a new dimension. After the outbreak in the city of Wuhan in China, the virus spread to most countries worldwide within a few months (BBC News, 2022). Due to the collapse of global supply chains on the one hand and a slump in demand (from customers) on the other, partly induced as a result of the lockdowns or retail closures introduced by many governments, numerous companies reported significant sales losses in 2020 (Nicola *et al.*, 2020). Share prices in various countries' stock markets also initially plummeted following the announcement of the first confirmed COVID-19 cases (Shehzad *et al.*, 2020). In the days and weeks that followed, stock prices gradually recovered, and at the end of 2020, i.e., the broad-based S&P 500 index even ended the year with a significant gain of over 16% (Macrotrends, n.d.). The performance of share prices has varied significantly in some cases, depending on the companies under review. Some companies appear to be the big losers of the crisis, while others quickly reached or even surpassed their original pre-crisis highs (Mazur *et al.*, 2021). The reasons for these differences are manifold and seem to depend on the sector and market of operation. Studies from He *et al.* (2020) and Mazur *et al.* (2021) showed that the sectors developed differently over time, and further development of the COVID-19 spread.

The COVID-19 outbreak and spread consist of several sudden, unexpected shocks affecting stock returns. Immediately after the first positive COVID-19 cases were confirmed in different countries and at the latest with the official declaration of the pandemic state by the WHO on March 11th, 2020, significant uncertainty in the markets about the further course of the spread of the disease and the associated economic and social implications was induced (Boone, 2020).

Based on previous research, there is ample evidence that uncertainty and insecurity in the stock markets may lead to an initial sell-off, particularly of riskier asset classes (Dzielinski, 2012). Investors tend to overreact in situations of more significant uncertainty (Brown *et al.*, 1988) while exaggerating their personal assessment of future development (De Bondt & Thaler, 1985; Seok *et al.*, 2024). Following unexpected events and negative news, individual investors react more sensitively to sentiment (Barber *et al.*, 2014; Chung *et al.*, 2016). For institutional investors, an initial sell-off can develop into a ripple effect, as high liquidity is essential for them in times of falling prices (Bernardo & Welch, 2004).

For the COVID-19 pandemic, it can also be argued that the events and course of the spread of COVID-19 differ from those of other shocks. On the one hand, the personal, social, and economic impact is much more far-reaching than in many comparable situations. Even the terrorist attacks of September 11th, 2001, had no actual material impact on the private lives of such a large number of people. On the other hand, a pandemic with a largely uncontrollable course, spreading at the speed and dynamic of a new dimension, is particularly suitable for spreading fear, uncertainty, and panic.

This leads, in turn, to two assumptions. First, the panic-like reaction following COVID-19 events should be observable, not only for broad market indices but also for individual companies. Second, investors will react more sensitively with a substantial, negative reaction due to the potential impact on their personal economic situation. Previous research suggests that retail investors, in particular, tend to make sentiment-driven decisions (Hsieh *et al.*, 2020), which makes an increased focus on this target group useful. For broad-based market portfolios of different countries, it has already been shown in the context of the COVID-19 outbreak that it led to negative, abnormal returns (Ali *et al.*, 2020; Rahman *et al.*, 2021).

Numerous events occurred during the COVID-19 outbreak and spread, all of which could represent potential shock situations for individual investors or groups of investors. The focus of this study is on three specific events, which have been identified as part of the research design (Chapter 5.2.1). These three significant events likely represent shock situations in the context of the spread of COVID-19 worldwide, particularly in the US, due to their importance and (financial) implications for the local economy and society. For these events, it can be assumed that the market participants had no prior knowledge and that the events were, therefore, actually unexpected:

- The official confirmation of the first positive COVID-19 case in the US on January 21st, 2020.
- The declaration of the COVID-19 outbreak as a "Public Health Emergency" on January 31st, 2020.
- The official declaration of the COVID-19 outbreak as a global pandemic by the World Health Organization on March 11th, 2020.

The hypotheses are therefore formulated as follows (Return Hypotheses):

H2a: The disclosure of the first COVID-19 case in the US leads to negative abnormal returns on stocks of companies included in the S&P 500 index.

H2b: The declaration of the COVID-19 outbreak as a public health emergency in the US (American Hospital Association 2020) leads to negative abnormal returns on stocks of companies included in the S&P 500 index.

H2c: The World Health Organization's declaration of a pandemic leads to negative abnormal returns on stocks of companies included in the S&P 500 index.

3.3 General Effect of the Release of Information about COVID-19 on Stock Volatility

Several aspects found in previous research serve as foundations for the hypothesis regarding the effect of information about COVID-19 on stock volatility in this dissertation. First, higher volatility after disclosing new information can be seen as an indicator of stock market efficiency (Chen *et al.*, 1999; Tweneboah-Koduah *et al.*, 2020). In line with the concept of EMH, investors' expectations are based on an analysis of the company's fundamental data or the market under consideration. Even if the fundamentals of companies initially remain unchanged after an exogenous shock situation, such as the COVID-19 outbreak, the market environment and outlook for companies operating in the affected markets change. Irrespective of whether investors adjust their expectations rationally and sell the security because the reservation price has fallen short or show an irrational reaction to the unexpected event and sell in a panic, this will result in increased volatility. As demonstrated by Berkman *et al.* (2011), already the perceived likelihood of a sudden disaster occurrence causes an increase in volatility and the risk premium for securities. In turn, exogenous shocks, disclosing sudden, unexpected information, should lead to changes in volatility levels, assuming that this volatility can also be measured at the company-specific level.

Second, uncertainty in expectations concerning a company's stock is closely linked with increasing volatility (Su *et al.*, 2019). Furthermore, also the emergence of uncertainty and instability in society is closely linked to rising volatility in the financial markets (Tetlock, 2007; Corbet *et al.*, 2018).

Third, a study by Engelhardt *et al.* (2021) concluded that societal trust and trust in the country's government are essential factors influencing volatility. Their study showed that the volatility of securities in countries with more trusted governments is lower than in countries with less trust. In general, there is evidence that political uncertainty has an impact on the volatility of different asset classes (Fang *et al.*, 2019; Wang *et al.*, 2019; Wang *et al.*, 2020) and that, conversely, political measures can reduce volatility, especially in the event of pandemic disease outbreaks (Bai *et al.*, 2020). A study also shows that the volatility of US equities is sensitive to positive or negative news in different industries (Baek *et al.*, 2020).

Fourth, investor sentiment also impacts the volatility of securities in general (Reis and Pinho, 2020). Lee *et al.* (2002) show that a shift to more negative sentiment leads to increased volatility. In some studies, volatility indices such as the Volatility Index (VIX) are even used as a measure of market sentiment themselves (So and Lei, 2015; Ding *et al.*, 2021). The authors argue that an increase in the VIX can indicate increased uncertainty and a more pessimistic mood, leading, in turn, to higher volatility. However, just as increased volatility can be interpreted as a sign of uncertainty and, therefore, pessimism, in some cases, a high level of optimism also indicates increased trading activity and greater exploitation of market potential. This can be observed, for example, in the price performance of cryptocurrencies in the course of individual events that are generally positive (Sapkota, 2022). Even if it is not fully transparent whether volatility can be seen as a sign of more positive sentiment and increased occurrence of irrational market forces or vice versa, changes in volatility should become visible and measurable when investor sentiment changes.

There is already evidence of an increase in volatility after the outbreak of the COVID-19 pandemic for broad market indices or market portfolios (Bai *et al.*, 2020; Haroon & Rivzi, 2020; Baker *et al.*, 2020). In turn, Sharma *et al.* (2014) observed that the overall volatility of a market also impacts volatility at the individual company level as part of a spill-over effect. Accordingly, it can be expected that an increase in volatility due to the disclosure of unexpected information in the wake of COVID-19 should be measurable when determining the effect at the company-specific level, in particular, while considering the change in the conditional standard deviation induced through the investigated events. Thus, the following hypotheses are set (Volatility Hypotheses):

H3a: The disclosure of the first COVID-19 case in the US has an effect on stock price volatility for companies included in the S&P 500 index.

H3b: The declaration of the COVID outbreak as a public health emergency in the US (American Hospital Association 2020) has an effect on the stock price volatility of companies included in the S&P 500 index.

H3c: The World Health Organization's declaration of the pandemic has an effect on the stock price volatility of companies included in the S&P 500 index.

3.4 Moderating Effect of Investor Sentiment on the Relationship between Release of Information about COVID-19 and Stock Prices

The primary aim of the study is to deepen the understanding of the moderating role of company-specific investor sentiment during exogenous shocks such as the outbreak and spread of COVID-19. As explained in Chapter 2, investor sentiment refers to the consolidated attitude of investors towards a security. The fact that investor sentiment significantly impacts stock prices is widely documented (Fisher and Statman, 2000; Seok *et al.*, 2024). The phenomenon of investor sentiment can be observed not only when looking at overall markets or indices, but also individually for individual companies. DeVault *et al.* (2019) argue that market-wide sentiment indicators measure the changes in sentiment at a broad level, which no longer allows analysis of the individual development of the trading risk of individual companies. In addition, a company-specific view of sentiment allows for a more thorough analysis of individual characteristics of companies and, in the further course of the study, the characteristics of sectors in aggregated form. This detailed analysis is no longer possible when using a market-wide sentiment indicator. Seok *et al.*, for example, identified the effects at the company level for the Korean stock market (Seok *et al.*, 2019a; Seok *et al.*, 2019b). They also determined that positive investor sentiment towards a company leads to higher returns in the short term. One possible explanation for this phenomenon could be that investor sentiment stands for (in this case) positive expectations, which causes the security price to rise due to increased demand.

Investor sentiment could also play a role in a sudden shock situation. As the Return Hypotheses H2a – H2c demonstrate, a shock situation leads to negative, abnormal returns in the short term. This is likely caused by a sharp sell-off of securities due to a panic-like reaction to the sudden event. Studies have already shown that investor sentiment influences the return from securities in situations of uncertainty (Tetlock, 2007; Kaplanski and Levy, 2010; Birru & Young, 2022). Birru and Young (2022) show that the impacting role of investor sentiment is substantially more prominent in times of higher uncertainty relative to when uncertainty levels are at their means, which is confirmed by a similar study by García (2013). Tetlock (2007) showed that investors tend to overreact to events when sentiment is negative, leading to increased stock price discounts, even when the fundamental value remains unchanged. Furthermore, a study by Ryu *et al.* (2019) found that investor sentiment did exhibit a significant impact on stock returns during the financial crisis of 2008 and 2009 in the Korean market, which can be seen as an exogenous shock. In negative shock situations or when uncertainty increases, investors might not initially sell all securities in their portfolio. However, for rational reasons, they initially tend to prioritize divesting securities for which they hold the most pessimistic expectations regarding future performance. Investor sentiment could be a differentiating factor for such situations. It can be assumed that in an exogenous shock, investors will initially sell securities for which their attitude is (more) negative than for other securities held. This would mean that companies with similar business models and fundamentals but different sentiment levels could react differently to exogenous events. As positive investor sentiment also positively affects security prices on "normal" trading days (Fisher and Statman, 2000; Brown & Cliff, 2005), this observation should also apply after shock situations according to the same logic. Accordingly, although negative abnormal returns occur in the context of sell-offs, these are not as strong for securities with a predominantly positive investor sentiment as for securities with a more negative investor sentiment. Yu and Yuan (2011) argue that, while rational traders need a defined compensation for a given risk, sentiment-driven traders could assess this risk compensation differently due to their sentiment bias and distort the risk-return relationship by asking for a lower price of risk.

As part of an investigation into the COVID-19 pandemic and its impact on the US and European securities markets, Reis and Pinho (2020), as well as Sun *et al.* (2021) in a study of the Chinese securities market, found initial indications that investors are sensitive to the number of cases in the respective countries (albeit to varying degrees), which further supports the assumption. According to Sun *et al.* (2021), these sensitive reactions cannot be based solely on economic indicators, indicating an influence of investor sentiment. Such a correlation should also be recognizable in a company-specific calculation of investor sentiment, and this effect should also be transferable to other securities markets in other countries. Therefore, the following hypotheses are proposed (Moderating Effect Hypotheses):

H4a: Investor sentiment moderates the relationship between the release of information about the first COVID-19 case and the stock prices of companies included in the S&P 500 index.

H4b: Investor sentiment moderates the relationship between the release of information about the declaration of the COVID outbreak as a public health emergency in the US (American Hospital Association, 2020) and the stock prices of companies included in the S&P 500 index.

H4c: Investor sentiment moderates the relationship between the release of information about the declaration of the pandemic by the World Health Organization and the stock prices of companies included in the S&P 500 index.

The four stages of the dissertation, including the hypotheses assigned to each, are summarized in Figure 4.

Stages	**Hypotheses**
Stage 1 - Determination of the company-specific sentiment indicators - Determination of the sector-based sentiment indicators - Determination of the aggregated overall sentiment indicator (OSI) - Testing the OSI for predictive accuracy for daily stock returns.	H1
Stage 2 - Investigation of the impact of the defined events on stock prices - Determination of CARs	H2a - H2c
Stage 3 - Investigation of the impact of the defined events on stock price volatility	H3a - H3c
Stage 4 - Investigation of the role of investor sentiment in the development of CARs during the defined events.	H4a - H4c

Figure 4. Sequence of the Investigation

Source: own compilation.

Chapter 3 develops the hypotheses of the dissertation from a synthesis of theoretical principles, previous findings from empirical research, and the research questions as formulated in Chapter

1. The hypotheses form the basis for the selection of suitable empirical research approaches in the following chapters. The hypotheses are tested using statistical methods, and the empirical results are analyzed and interpreted in Chapter 6. The investigation sequence is summarized in Figure 4, comparing research stages and hypotheses. An overview of the Research Questions, related hypotheses, stages, and the corresponding chapters of the dissertation is provided in Appendix A.

CHAPTER 4
METHODOLOGICAL FOUNDATIONS

This chapter provides a scientific and methodological overview of the econometric and statistical methods applied in this study. First, various types of sentiment indicators are discussed in detail. Then, based on the indicators' characteristics, advantages, and disadvantages, the sentiment indicator used for this study is selected. Subsequently, the construction of the chosen sentiment indicator, in which several econometric methods are used, is discussed in detail. Various econometric methods are used in the present study to ensure that the research questions investigated are answered scientifically. To calculate the investor sentiment indicator based on the approach developed by Seok *et al.* (2019b), the linear regression method and principal component analysis were used. To determine the prediction reliability of the aggregated Overall Sentiment Indicator (OSI) for S&P 500 index daily returns (Predictive Hypothesis, H1), Granger's test for causality is applied. The event study method is used to test hypotheses H2a, H2b, and H2c (Return Hypotheses). The generalized sign test is used for the significance test. For further analysis of hypotheses H3a, H3b, and H3c (Volatility Hypotheses), a GARCH model is first specified, and the significance test is then carried out using a cross-sectional t-statistic based on an approach by Savickas (2003). Finally, to test hypotheses H4a, H4b, and H4c (Moderating Effect Hypotheses), the U-Mann-Whitney test and a median test were applied.

4.1 The Measurement of Investor Sentiment

Investor sentiment is complex and thus difficult to determine (McGurk *et al.*, 2020) and is sometimes influenced by many invisible factors or factors where a connection does not seem obvious. Due to the "non-tangible" character of investor sentiment, it is essential to select the appropriate operationalization in the form of a suitable model for measuring investor sentiment as part of the research project preparation to effectively exclude possible sources of error and confounding variables from the outset.

Sentiment indicators can be classified according to the underlying data or individual indicators, the so-called proxies, which represent an operationalization of investor sentiment and form the basis for calculating the corresponding indicator. Bu (2021) distinguishes direct and indirect measures, with direct measures mainly based on direct opinions and indirect measures derived from other data or KPIs. According to Zhou (2018), approaches to operationalizing investor sentiment can be classified into three categories: survey-based, text- and media-based, and market-based.

As described in the context of theory development, various approaches exist to measure investor sentiment in markets, indices, or individual companies. A common fact of these approaches is that their operationalization can only ever approximate the actual sentiment of market participants as closely as possible. After all, "real investors and market [...] are too complicated to be neatly summarized by a few selected biases and trading frictions" (Baker & Wurgler, 2007). Therefore, investor sentiment can only be "an approximate measurement of the stock market's attitude at a given time" (Gallant, 2017). Even if this statement is valid, a wide variety of approaches have proven their suitability for predicting, for example, future stock returns or the volatility of securities, at least based on the usual significance levels.

However, some of the approaches were criticized because the metrics considered are basically the result of investor sentiment. The IPO first day returns, for example, used by Baker and Wurgler (2006) in their study, result at a certain level precisely because the investor's attitude towards this security is mainly positive or negative. Qiu and Welch (2004) therefore raise the question "how does one test a theory that is about inputs and outputs with an output measure?“ Although the approach developed by Baker and Wurgler, as described later in the chapter, predominantly considers "outputs" for measuring investor sentiment, it has received widespread recognition to date and has been revisited in several studies (Corredor *et al.*, 2013).

In addition to operationalizing investor sentiment, the question of measuring sentiment at the company level is also coming to the fore in more recent research. Increased data availability and the assumption that investor sentiment can vary not only between markets but also between companies have prompted several studies to address this topic (Seok *et al.*, 2019b). The first approaches of this kind initially attempted to link market-related sentiment measurements with company-specific problems (Bergman & Roychowdhury, 2008; Hribar & McInnis, 2012; Livnat & Petrovits, 2011; Mian & Sankaraguruswamy, 2012; Walther *et al.*, 2013), which, however, disregards company-specific characteristics, at least when measuring sentiment. RQ3 asks about the suitable methods of measuring IS on a daily and company-specific basis. In this chapter, the various approaches will be systematized and characterized.

4.1.1 Survey-based Sentiment Indicators

Survey-based indicators are used in numerous studies as a proxy for investor sentiment (Fisher & Statman, 2000; Qiu & Welch, 2004; Greenwood & Shleifer, 2014; Amromin & Sharpe, 2014). On the one hand, measuring investor sentiment via a direct survey of market participants offers the advantage over other approaches of direct, fast, and transparent availability of sentiment information. In contrast to other approaches, sentiment is not "operationalized" but directly available. On the other hand, disadvantages lie in the time-consuming data collection and the limitations in sample size, sample selection, and survey frequency (Zhou, 2018). Also, the risk of socially desirable answers or the emergence of the so-called "prestige bias", in which respondents give personally positive answers (Beer & Zouaoui, 2013), must be considered. Furthermore, it is questionable whether all market participants know their attitude towards a particular security or market precisely because "sentiment" is an unconscious phenomenon. Therefore, survey-based measures are considered “less objective” (Bu, 2021).

In a review by Zhou (2018), mixed results for survey-based indicators’ potential were found, with the predictive accuracy appearing to depend primarily on the number of people surveyed and the time horizon of the surveys conducted. Nevertheless, Zhou (2018) states that the possibilities offered by the Internet and the ability to conduct surveys via smartphones could make determining sentiment via surveys more important in the future. In this context, Chau, Deemonsak, and Koutmos (2016) determined that sentiment-driven investors consider survey-based indicators when making investment decisions. It is also worth noting that survey-based indicators are particularly used as robustness checks in addition to other indicators (Colón-De-Armas *et al.*, 2017). Well-known “ready-made”, survey-based proxies for investor sentiment are the UBS/ Gallup sentiment survey or the weekly American Association of Individual Investors Investor Sentiment Survey (Maknickiene *et al.*, 2018).

4.1.2 Text- and Media-based Analytic Indicators

Text- and media-based indicators represent another category of sentiment indicators, with news-analytical indicators forming an important sub-category. This frequently chosen method of determining investor sentiment is an analysis based on categorizing current opinion statements from various stakeholder groups - usually from institutional analysts or private shareholders. An overall sentiment for individual companies up to entire markets is thus determined from a suitably large sample. The source of the news is diverse. Traditionally, analyst reports and newspaper commentaries (Garcia, 2013; Mangee, 2018; Baker *et al.*, 2020; Fisher & Statman, 2000) have predominantly been analyzed in more detail to determine sentiment. Both the sentiment and the surprise index from Marketpsych by Thomson Reuters also used text-based measurements built from many sources of the investment and business sector (Bu, 2021; Papakyriakou *et al.*, 2019). Since the early 2010s, the analysis of Internet-based news and social media posts, such as Twitter posts (Bollen & Mao, 2011; McGurk *et al.*, 2020; Sanford, 2022; Zeitun *et al.*, 2023), Facebook posts (Karabulut, 2013), Reddit Posts (Lyócsa *et al.*, 2022; Bowden & Gemayel, 2023) or Google search queries (Lyócsa *et al.*, 2020; Reis & Pinho, 2020; Chen *et al.*, 2021), has increasingly come to the fore. In the case of Google search query analysis, the studies rely on analyzing Google content and determining sentiment based on the search frequency of specific terms or combinations of terms over time.

After an initial survey, the content of the opinion expression is evaluated according to the direction of sentiment (positive, neutral, or negative, in some cases, also scale-based, further gradations). Dictionaries or lexicons are used to assign those emotion scores to the words (Shapiro *et al.*, 2022; Garcia, 2013). In a 2011 study, Mao examined the usability of various internet-based operationalization approaches for investor sentiment. The author showed that both the analysis of Google queries and the analysis of Twitter postings can be used to predict the stock returns of the Dow Jones Industrial Average (Mao, 2011). Critical to the success of using social media streams as sentiment indicators is, first, the use of a sufficiently large sample size, a reliable determination of the direction of sentiment from the postings, and ensuring that there are "real" people behind the postings who, if possible, are themselves active in the securities markets (Bu, 2021).

Another approach, which combines the "traditional" method of text-based sentiment determination using daily published articles with the use of modern software tools to determine the direction and strength of sentiment as accurately as possible, was presented as the Daily News Sentiment Index by Shapiro, Sudhof, and Wilson (2022). This Index shows a prediction accuracy at the level of survey-based sentiment analysis methods (Figure 5).

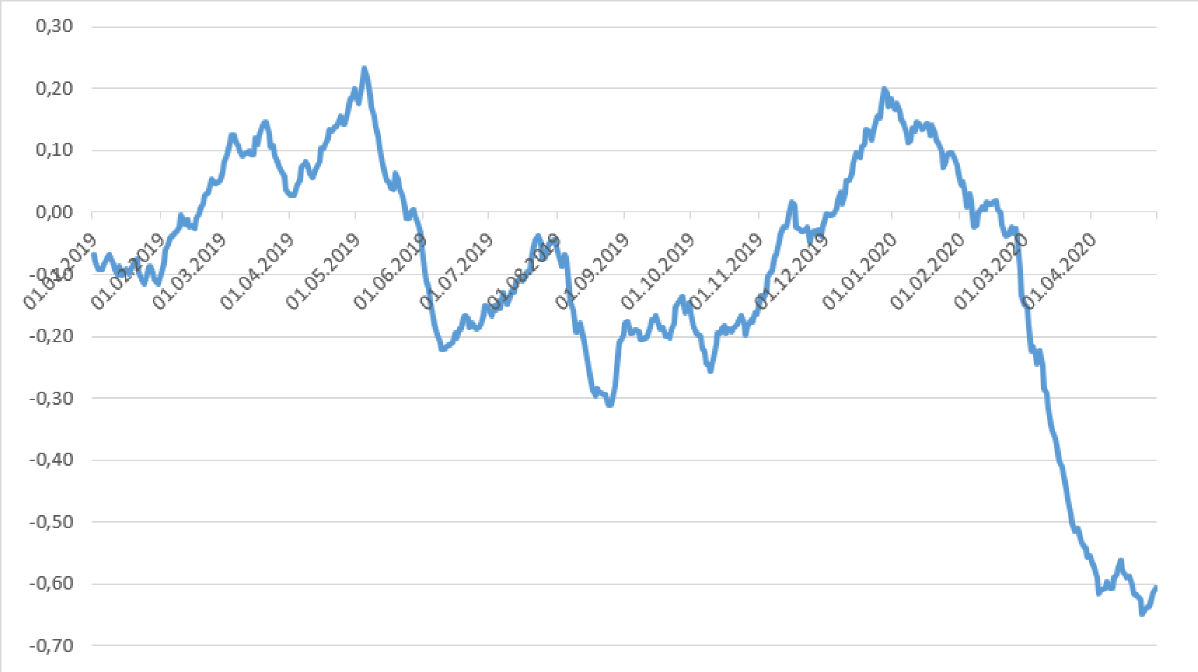

Figure 5. Daily News Sentiment Index Around the COVID-19 Outbreak

Source: own compilation based on data from the Federal Reserve Bank of San Francisco, https://www.frbsf.org/research-and-insights/data-and-indicators/daily-news-sentiment-index/ (as of 25th of August, 2024).

While analyzing the role of investor sentiment during the outbreak of the COVID-19 pandemic, the focus of the research was initially on sentiment following COVID-19-related news and its influence on the development of share prices or the volatility of securities, whereby text- or media-based indicators were predominantly used for measurement. For example, the Google Search Volume Index was used for this purpose, in which individual search terms were assigned a positive or negative alignment (Cevik *et al.*, 2022).

In other studies, a keyword analysis in Google Trends was used to construct a "COVID-19 fear index" as an investor sentiment proxy (Subramaniam & Chakraborty, 2021; Anastasiou *et al.*, 2022). Sun, Bao, and Lu (2021) used individual opinion statements from the Chinese investor social platform Guba to build the GubaSenti index.

4.1.3 Market-based Indicators

Contrary to the other types of sentiment indicators, market- or ratio-based indicators are characterized by high reliability and unambiguity in their determination and, at the same time, broad data availability. They are based on one or a combination of several indicators, which in themselves are demonstrably suitable as an operationalization for the prevailing sentiment, such as closed-end fund discount (Baker & Wurgler, 2006; Colón-De-Armas *et al.*, 2017), stock exchange turnover, equity shares in new issues or dividend premiums (Baker & Wurgler, 2006). The final investor sentiment index is then often calculated as the difference between a theoretical expected value (often operationalized as the vector of residuals) and the actual observed proxy value (Zhou, 2018).

To improve the prediction accuracy of the proxies, different investor sentiment indicators use a combination of various individual measures as a composite IS index based on the principal components of the individual proxies. Baker and Wurgler used the closed-end-fund discount, NYSE share turnover, the number of IPOs, the average first-day returns on IPOs, and the equity shares in new issues as the dividend premiums to build their index (Baker & Wurgler, 2006). Based on this approach, Seok *et al.* (2019a) developed a similar indicator, using different market indicators (Relative Strength Index, Psychological Line Index, logarithm of the trading volume, and the adjusted turnover rate) and a principal component analysis to build a daily, company-specific sentiment index. They used the residuals of a regression of the individual components against the general market return (for the market where the companies are listed). Regressing stock price movements against market returns or other macroeconomic factors (e.g., GDP, long-term interest rates, Consumer Price Index) is generally a common approach to distinguish rational from irrational price movements (Uygur & Tas, 2014).

In general, a broad distinction of market-based indicators can be made based on the level of aggregation under consideration:

- Country-specific indicators
- Market / index-specific indicators
- Sector-specific indicators
- Company-specific indicators

"Index-based indicators" can be seen as a sub-category of the market-based indicators. These are simplified and “ready-made” into an index figure based on an underlying calculation methodology. Numerous providers offer different indices whose objectivity, validity, and reliability, and thus suitability as an operationalization for investor sentiment, have been proven in part by corresponding studies. Among the most prominent providers are Ravenpack (Hafez & Xie, 2016), the Bear Sentiment Index (Bu, 2021), and, for example, the empirically derived sentiment index of the two researchers Malcolm Baker and Jeffrey Wurgler (Arif, 2014; Corredor *et al.*, 2013; Mian & Sankaraguruswamy, 2012). The main drawback of those ready-made indices is the non-disclosure of the exact calculation formula of the indicator by the publishing body. Thus, it is not transparently comprehensible which factors or which weightings of various elements were applied to create a sentiment value. Especially in connection with the essential fact mentioned above that the determination method of sentiment must be adapted to the research question, this lack of transparency may be problematic. On the other hand, the advantage of these "prefabricated" factors is their uncomplicated availability and easy applicability for research purposes. During investigations into the COVID-19 pandemic, these “ready-made” indices also offer the advantage of consistent availability at any frequency and being tailored to the desired sample size, from individual companies and specific sectors to large markets.

4.2. Sentiment Indicator Used for This Study

The following section is dedicated to deriving the sentiment indicator used for the present study from the broad selection of available indices in the various categories. The respective approaches are more or less suitable for different investigation purposes. Therefore, selecting a suitable determination methodology is essential for the meaningfulness of the investigation result against the background of the object to be investigated. Thus, the content of this subchapter, aimed at selecting a specific sentiment indicator, directly relates to Research Question 5 (RQ5).

4.2.1 Selection Criteria for Calculating the Investor Sentiment Indicator

Research Question 5 (RQ5) seeks to identify the most suitable method of measuring investor sentiment in the context of this study. A sentiment indicator must meet several criteria to be suitable for this study. First, this thesis focuses on the impact of COVID-19 on investor sentiment for US companies in various sectors and the role of investor sentiment in moderating the relationship between the outbreak of COVID-19 and company stock prices. As a result, the most appropriate indicator is a company-specific investor sentiment indicator. In this case, indicators measuring broad market indices or countries' sentiments cannot be applied. In principle, indicators from each of the above-presented categories provide company-specific investor sentiment measures. As such, they fulfill this criterion and seem suitable for the present study.

Second, a quality criterion to ensure valid and reliable results is to avoid a spill-over effect between the companies and sectors under review, with the sentiment from one company or one sector affecting other companies in the same or different sectors because of an economic relationship. Although these spill-over effects can never be entirely ruled out, they have been reported particularly for news-based indicators, especially against the backdrop of shock situations (Long & Zhao, 2022). This finding is underlined by a study by Cohen and Frazzini, who demonstrated a price effect in companies that have an economic relationship with each other in situations where relevant news occurs at an affiliated company (Cohen & Frazzini, 2008).

Third, the boundary condition of the present study is the need for the broad availability of a uniform sentiment indicator on a daily basis. Some studies make use of prefabricated text- or survey-based sentiment indicators developed by companies (Refinitiv, Ravenpack, and others; Chapter 4.1), presumably due to the easy accessibility and availability of the data. However, in many cases, the availability of these indicators is limited to popular companies or companies with a large market capitalization, and their composition and data basis are often not transparently accessible. To ensure broad data availability also for smaller or less "well-known" companies as well as to guarantee the traceability of the study results, it, therefore, makes sense to go for a market-based indicator based on generally available key figures that can, thus, in case of doubt, be generated for each company under consideration from freely accessible data. In addition, a rising number of researchers have highlighted concerns that ready-made text-based or survey-based indices may fail to sufficiently account for the irrational aspects of investor expectations (Pham *et al.*, 2025; Ung *et al.*, 2024), and may also be affected by methodological limitations, such as sample selection bias (Zhou, 2018). Consequently, market-based indices are often considered to provide a more objective measure of investor sentiment (Aggarwal, 2022; Pham *et al.*, 2025).

Fourth, this dissertation’s added value comes precisely from the intensive development and application of a sentiment indicator, which is why using a “pre-calculated” index is not useful. Finally, this study aims to examine the development of investor sentiment for a defined period in more detail by investigating the underlying drivers, which would also not be possible using a “ready-made” indicator.

To sum up, even though many studies analyze the impact of investor sentiment on share prices using, e.g., text-based measures, this dissertation chooses to use a market-based indicator. Examining the suitability of such an approach for the research questions at hand also represents an added value of this dissertation.

4.2.2 The Daily Company-Specific Sentiment Indicator

Seok, Cho, and Ryu (2019a) propose a daily, company-specific investor sentiment indicator (IS) based on a combination of several financial market metrics related to corporate investor sentiment (investor sentiment proxies). This extends an initial approach by Yang and Zhou, which initially aimed at generating a proxy based on commonly available metrics (Yang & Zhou, 2015). A similar approach is also used in further research by Ryu *et al.* (2017) and Yao and Li (2020).

The IS construction is similar to the investor sentiment indicator proposed by Baker and Wurgler (2007). However, it uses other individual proxies. Moreover, it supplements Baker and Wurgler's approach with aspects that are particularly helpful for this study's research questions, i.e., on the one hand, it offers lagging elements that provide consistency and tend to develop more slowly over several trading days (e.g. Relative Strength Index and Psychological Line Index), and on the other hand, by taking into account the daily trading volume and the adjusted turnover rate, the formula includes proxies that take into account the short-term nature of an exogenous shock. This takes into account the fact that in "normal" times, sentiment tends to adapt to a changed market or company situation in the medium term and with a specific time lag, while at the same time retaining the flexibility required to analyze a shock situation.

All individual proxies are combined to generate the indicator using a principal component analysis (based on the Baker / Wurgler proposed variant for determining a sentiment indicator). The principal-component analysis is intended to level out the weaknesses of the separate proxies and thus increase the measurement accuracy of investor sentiment (Liu *et al.*, 2020). The following components are used to generate the sentiment indicator:

- Relative Strength Index (RSI)
- Psychological Line Index (PLI)
- Adjusted Turnover Rate (ATR)
- Logarithm of Trading Volume (LTV)

Finally, the PCA outcomes are combined using a linear function to generate the IS indicator (based on the Baker and Wurgler proposition for determining a sentiment indicator).

The Relative Strength Index (RSI)

The relative strength index (RSI) is a financial market indicator that provides insight into the relative strength of a market and thus gives statements on the "overbought" or "oversold" status of a stock. The RSI itself is defined as

$$RSI_{i,t} = \left[\frac{RS_{i,t}}{1+RS_{i,t}}\right] \cdot 100\,,$$

where

$$RS_{i,t} = \frac{\sum_{k=0}^{13} max\left(P_{i,t-k} - P_{i,t-k-1}, 0\right)}{\sum_{k=0}^{13} max\left(P_{i,t-k-1} - P_{i,t-k}, 0\right)}$$

The RSI determines if a stock or index is overbought or oversold in a certain period. The RSI is thus a lagging indicator, as it moves based on observing a stock's past behavior. In many investigations, the 14-day RSI is used, which includes the market development in the past 14 trading days in its calculation.

The RSI was applied in several studies as an operationalization for sentiment. In 2008, Chong and Ng proved that a trading strategy based on the RSI generates better returns than the buy-and-hold strategy (Chong & Ng, 2008). For the first time, Chen *et al.* (2014) used the RSI as a proxy for an explicit sentiment measure in 2010 in a study of the Chinese stock market. The indicator, which was developed from six individual components, showed "good out-of-sample predictability".

Subsequently, several investigations demonstrated the suitability of the Relative Strength Index as a proxy for investor sentiment in studies of the stock/ securities market (Kim & Ha, 2010; Phoung, 2021), while another study demonstrates the suitability of the RSI for the futures market as well (Gao & Liu, 2020).

The Psychological Line Index

The Psychological Line Index (PLI) is another index used to indicate market conditions and momentum. It counts the number of upward movements during a predetermined period and captures short-term price reversals and the psychological stability of investors. The PLI is calculated by considering the proportion of individual subperiods in the overall period under consideration in which prices rose. The calculation of the PLI is based on the following formula:

$$PLI_{i,t} = \left[\sum_{k=0}^{11}\left\{\frac{max(P_{i,t-k}-P_{i,t-k-1},0)}{P_{i,t-k}-P_{i,t-k-1}}\right\}/12\right]\cdot 100.$$

A PLI with a value between 50 and 100 thus indicates that the number of subperiods with higher closing prices than starting prices was in the majority. In contrast, a PLI between 0 and 50 indicates a situation of subperiods with predominantly lower closing prices (Murphy, 1999). For the interpretation of the index, this means that in the case of a value between 50 and 100, buyers dominate the market, while at a lower value, sellers dominate the market. Furthermore, at a value of 75 and higher, the market or the company under consideration is considered overbought, while a value of less than 25 indicates "oversold". For this reason, PLI can be interpreted as an indicator of prevailing sentiment.

It should be noted that the PLI merely reflects the proportion of positive subperiods in the total number of periods and, therefore, does not indicate the total gains or losses in the period under review. At the same time, this statement reveals a weakness of the Psychological Line Index when used as an indicator of investor sentiment: experiencing few individual subperiods with high losses in the period under review, accompanied by a large number of positive periods with small gains, can in total lead to a "bullish" indicator, while the security price fell in the same period. Also, the choice of the appropriate period and the determination of the length of a single period are essential for the success of an investigation. In the context of their study, Ryu *et al.* rely on a total period of 12 trading days with an individual subperiod length of one trading day (Ryu *et al.*, 2017).

Numerous other studies also use the Psychological Line Index as a proxy for investor sentiment. It is used either as a stand-alone indicator (Jaziri & Abdelhedi, 2018; Phuong, 2020) or with other financial indicators (Liu *et al.*, 2020; Yang & Chi, 2021). The Psychological Line Index has also been used in a study to measure investor sentiment in the futures market (Gao & Yang, 2017).

Logarithm of Trading Volume (LTV)

The trading volume of a share is closely linked to its liquidity. Liquidity results from the “realizability of a share,” i.e., the ability to be absorbed by a market without losses (Pagano, 1989). A market's increased ability to absorb shares in the short term, in turn, makes it more attractive to market participants, resulting in higher market activity. The activity of a market can be determined by the trading volume (Pagano, 1989).

Baker and Stein (2004) found a relationship between investors' optimism and liquidity in the market. Scheinkman and Xiong (2003) also argue that heterogeneous beliefs based on investors' overconfidence lead to increased speculative trading among market participants, which, in turn, increases trading volume.

In line with these findings, Liu proves in a more recent study that trading volume and investor sentiment are linked (Liu, 2015). Moreover, the author argues that the basic behavioral finance theory, the concept of "noise trading," also implies increased trading activity when market sentiment is correspondingly positive. The author also argues, based on the findings of a study by Odean and also in line with Scheinkman & Xiong (2003), that high investor sentiment and, consequently, high self-confidence among securities market players leads to high stock liquidity (Liu, 2015; Odean, 1998).

Two other studies also demonstrated that Twitter messages or news from a real-time stock ticker can serve as a proxy for investor sentiment at the firm-specific level to predict higher trading volume (of the S&P 500 index, among others). Accordingly, it can be assumed that higher trading volume is significantly related to positive investor sentiment and that this also allows for drawing further conclusions about the development of stock prices in future periods (Duz Tan & Tas, 2021; Joseph *et al.*, 2011).

In contrast to these findings, a study by Kim, S.H., and Kim, D. (2014) found no correlation between investor sentiment extracted from internet postings on the Yahoo Finance portal and the trading volume of the investigated companies, nor with the future stock returns of the companies studied. In contrast to previous studies, they used a longer time horizon of six years and a broader sample of 91 companies and 32 million downloaded text messages to answer their research questions. Investor sentiment was determined at individual company and aggregate levels (Kim & Kim, 2014). In a study on the Johannesburg Stock Exchange, trading volume was also used as an investor sentiment indicator to predict the volatility of stock prices. The study's authors could infer the further development of securities volatility based on the development of trading volume (Rupande *et al.*, 2017).

Additionally, in the study by Siganos, Vagenas-Nanons, and Verwijmeren (2017), the authors identified another significant relationship between investor sentiment and trading volume. The study examined how substantial divergence and dispersion of sentiment affect trading volume.

Specifically, it was possible to determine and prove that in situations with a high divergence of sentiment, trading volume was higher following the release of both positive and negative company news than in situations with greater homogeneity of sentiment (Siganos *et al.*, 2017). In this dissertation, the LTV was calculated using the following formula:

$$LTV_{i,t} = ln(V_{i,t}).$$

Adjusted Turnover Rate (ATR)

Baker and Wurgler propose using the Turnover Rate as a proxy for measuring investor sentiment as part of their comprehensive study. The turnover rate does not provide any information on the direction of sentiment. The reason is that it is not possible to clearly state whether increased turnover was caused by positive or adverse investor sentiment. To make the ratio more manageable, Zhang and Yang in 2014 finally proposed the use of the "adjusted turnover rate," which can be defined as described by the following formula (Yang & Gao, 2014):

$$ATR_{i,t} = \frac{V_{i,t}}{number\ of\ shares\ outstanding_{i,t}} \cdot \frac{R_{i,t}}{|R_{i,t}|}.$$

Beyond its original use as a financial indicator, the turnover rate's usability as a sentiment indicator was confirmed in another study on the securities market and a study focusing on the futures market (Gao & Liu, 2020; Gao & Yang, 2017). Furthermore, the suitability of shares outstanding as a proxy to predict stock returns has also been empirically proven (Nelson, 1999).

Calculation of The Company-Specific Sentiment Indicator

The next step in developing the overall sentiment indicator is to determine the residuals of the four individual components on a daily basis by regressing the daily values against a "risk-free market return". This is based on the assumption that the residuals, i.e., the unexplained portion of the variance of a value, represent the irrational component of the sub-indicators as an unexplained value contribution.

This is in line with the definition of investor sentiment, which precisely assumes that this type of sentiment is irrational and thus cannot be explained by typical models. Each stock return value must be adjusted for its "market share" to calculate the residuals. Again, this is based on the assumption that each trading day’s overall price gain or loss is not solely attributable to individual company considerations but that general market events and micro- and macroeconomic trends influence price movements. In order to finally measure a company's investor sentiment, each factor of the sentiment indicator must, therefore, first be adjusted for this market-induced component (Seok *et al.*, 2019a).

To do this, each individual component is now regressed based on the formula (Seok *et al.*, 2019b):

$$Comp_{k,i,t} = a_0 + a_i \cdot Market_t + \varepsilon_{k,i,t}$$

where $Market_t$ is the market excess return (i.e., market return less the risk-free rate) at time t. This results in four equations, one for each component. Residuals obtained from these equations are the isolated daily residuals of each of the four sub-indicators. These residuals form the basis for calculating the sentiment indicator.

For the final calculation of the daily, company-specific sentiment, the next step is to calculate a Principal Component Analysis (PCA) for each of the calculated partial values (ultimately four PCAs per company examined) to reduce the dimensions and further condense the collected data systematically. This approach was proposed initially by Baker and Wurgler (2007) and was subsequently used in numerous studies (Chen *et al.*, 2014; Seok *et al.*, 2017; Aggarwal & Mohanty, 2018)

PCA is a mathematical method of multivariate statistics that structures extensive data sets using the covariance matrix's eigenvectors and simplifies a data set by reducing the linear combinations to principal components (Greenacre *et al.*, 2022). The PCA in the current investigation will be carried out using the statistical analysis software Stata. An eigenvalue of at least 1 is the threshold value for extracting a component.

For the final calculation of the daily sentiment indicator, the calculated principal components are now multiplied separately at the individual company level by the respective daily values for the individual indicators, and the results are finally added together:

$$S_{i,t} = F_{i,RSI} \times RSI_{i,t} + F_{i,PLI} \times PLI_{i,t} + F_{i,ATR} \times ATR_{i,t} + F_{i,LTV} \times LTV_{i,t}.$$

The resulting variable is a company-specific sentiment indicator, available daily over the observation period.

4.3 Granger's Test for Causality

Granger's test for causality, introduced by C.W.J. Granger in 1969, measures whether one time series is useful for forecasting another (Granger, 1969). The test is widespread and often used to analyze time series data in many fields (Shojaie & Fox, 2022).

Even though Granger speaks of "causal relationships" and tests the "causality" with his procedure, the test procedure is only based on the assumption of a flow of information between a variable y at time $t = 0$ and a variable x at a later time. Variable y is therefore considered causal for x if (past) values of y contribute to the explanation of x. An actual and direct causality cannot be proven using the test procedure, which is why "Granger causality" is also referred to as a fixed expression in this context.

The linear vector autoregressive model (VAR) originally developed by Granger is a bivariate model, initially not including any other influencing variables, leading to less precise results. More recent approaches, such as Network Granger Causality, solve this problem by considering additional variables or simultaneously determining the Granger causality of several time series (Shojaie & Fox, 2022).

The vector autoregressive model proposed by Granger, which is still, along with the Sims test (1972), among the most popular tests to measure Granger-causalities (Maziarz, 2015), is based on the following framework:

$$A^0 x_t = \sum_{k=1}^{d} A^k x_{t-k} + e_t,$$

where $A^0,\ldots,A^d$ can be described as $p \times p$ lag matrices and d denotes the lag or order, whereas e_t is the error term of the calculation (Shojaie & Fox, 2022). This basic autoregressive model uses x_{t-k} as predictors for x_t. To test the additional explanatory power of y in the development of x, the model is now specified further (Ding *et al.*, 2006):

$$A^0 x_t = \sum_{k=1}^{d} A^k x_{t-k} + \sum_{k=1}^{d} B^k y_{t-k} + e_t.$$

The Granger test for causality tests the null hypothesis $B^1 = B^2 = \cdots = B^d = 0$, indicating that the past development of y has no additional explanatory value for x. If at least one B^d would be significantly different from 0, y would be Granger-causal for x (Shojaie & Fox, 2022). The significance of the calculation can be determined using an F-test, including values of the reduced model (which only contains the values of the time series of x) in addition to the full model (which contains the values of both time series, x and y) (Shojaie & Fox, 2022):

$$F = \frac{(RSS_{red} - RSS_{full})/(r - s)}{RSS_{full}/(T - r)}$$

with RSS_{full} and RSS_{red} as the residual sum of squares for the full and the reduced models with r and s as parameters, respectively. As an alternative, the χ^2-statistic based on Wald statistics or on the likelihood ratio can be used (Cromwell, 1994).

According to Shojaie and Fox (2022), the "Granger direct test" (Maziarz, 2015) has various restrictions, as there are many underlying assumptions and requirements that need to be fulfilled to identify Granger-causal relationships with the described model reliably:

- continuous valued observations
- linearity
- stationarity
- perfect observation of the variables
- discrete sampling frequency
- known lag

The fulfillment of these criteria can be tested using various techniques. For example, to determine the regression coefficients, the lag maximizing the explanatory share of the analysis needs to be defined arbitrarily (Maziarz, 2015). The correct lag can be determined manually or supported by using the Akaike, Schwarz Bayesian, or Hannan-Quinn criterion. Additional tests, such as the Augmented Dickey-Fuller (ADF) procedure, can be used to check for stationarity (Agiakloglou & Newbold, 1992). In the case of non-stationarity of time series, the data can be reshaped. In the case of non-linearity, a non-linear form of Granger's test can be used (Ding *et al.*, 2016). Upstream tests such as Spearman's rank correlation test can pre-qualify the relationship between the variables to be analyzed and provide additional insights.

Samples, in reality, violate many of the assumptions mentioned. In addition, several authors (Harvey & Stock, 1989; McCrorie & Chambers, 2006) found that test results vary or might be misleading if samples are taken too rarely. For this reason, the model is not without criticism about its informative value; after all, it cannot be used to make a clear statement about causality between two variables. However, Granger's test for causality is popular for analyzing time series in finance, economics, and other disciplines such as neuroscience or climate science (Shojaie & Fox, 2022). One reason that might explain the popularity is the lack of theories on mechanisms between two variables potentially being in a causal relationship (Maziarz, 2015), resulting in analyzing a "simple" flow of information between the variables.

4.4 The Event Study as an Investigation Method in Capital Market Research

This dissertation uses the event study method to identify possible abnormal returns in the security prices. Abnormal returns are understood to be gains and losses that arise for investors due to a specific event and that exceed the expected, for example, the average securities return, which was also previously estimated within the framework of the event study (Fama *et al.*, 1969). The event study is not a stand-alone method. Instead, the method combines "various known statistical tools in the context of describing and explaining capital market reactions to substantively broadly similar particular events in the above sense" (Gerpott, 2009).

In addition to the historical development of the event study into an established and recognized research methodology, this section will also deal with the ideal-typical structure of such a study, suggestions for the systematization of event studies as well as the statistical test procedures used, the procedure of the statistical test procedures for checking the robustness as well as the significance test of the abnormal returns determined.

4.4.1 Economic Theories Underlying Event Study Methodology

In economics, event studies are predominantly used to examine the effects of economically relevant (firm-endogenous and exogenous) events on the value of firms, which, in the case of listed companies, can be determined based on the prices of their securities (MacKinlay, 1997). They represent a central and frequently used methodology in this context. Binder (1998) calls the event study "the de facto standard method for calculating the price behavior of securities in response to events [...]". By applying the event study methodology, on the one hand, the results of numerous studies offer important implications for companies, mainly related to information policy and shareholder communication. On the other hand, focusing on shareholders' reactions to events makes it possible to investigate market efficiency.

Event studies have a comparatively long tradition in the scientific examination of economic contexts, especially in the analysis of capital market prices. The majority of event studies investigate returns by examining companies' ordinary shares. However, other securities, such as corporate bonds or listed preference shares, are also used (Pauser, 2008).

A paper by Dolley (1933) is seen as the first event study conducted (MacKinlay, 1997), investigating abnormal returns in connection with stock split-ups on the New York Stock Exchange. With the increasing availability of large amounts of data (for example, on share prices, corporate events, and corporate reputation), the popularity of event studies continued to grow in the following years. Myers and Bakay (1948), as well as Barker (1956 and 1957), also investigated the impact of stock split-ups on market prices, while another study by Barker and an investigation by Ashley focused on the impact of a change in dividends on stock return (Barker, 1958; Ashley, 1962). In particular, the 1968 work of Ball and Brown, and the 1969 work by Fama, Fisher, Jensen, and Roll defined a standard for event studies that is still used today in a largely unmodified form. Both studies were the first to use the market model approach to determine a "fair value" of a share. Fama *et al.* (1969) used a regression of stock returns against market returns to determine the fair values of the shares and the expected "normal" returns. They then used the difference between the observed returns and the theoretical "normal returns" to determine whether abnormal returns occurred during the event under investigation. This was a further development of the accounting practices used to date, whose homogeneous principles did not allow any conclusions to be drawn about the actual financial condition of companies (Ball & Brown, 2014). According to Ball & Brown (2014), Fama *et al.* (1969) also changed the understanding of the relationship between share prices and information about events. Whereas previously, the focus was on the assumption that share prices develop emergently from a wide range of information about macroeconomic variables, Fama *et al.* concentrated on the effects of a specific event on share prices at different points in time (Ball & Brown, 2014). This rethink ultimately laid the foundation for the event study methodology. Further developments of the approach took place in the following years within the framework of the studies by Brown and Warner, among others (1980 and 1985), and by Kothari and Warner (2007).

Today, the event study is used in many contexts. According to Kothari and Warner (2007), 565 papers using event studies were published in major journals between 1974 and 2000, showing the popularity of this econometric framework. In economics, event studies are used, for example, in M&A processes after the announcement of news (i.e., of macroeconomic variables) or after the issue of new equity or debt (MacKinlay, 2007). In law, the impact of regulatory changes or legal cases on company value can be assessed (MacKinlay, 2007). Other applications are, for example, in history, marketing, or political science (Corrado, 2011). A literature review by Wang and Ngai (2020), analyzing 1219 papers related to event studies from

1983 to 2016, identified seventeen different “research clusters” covering various research questions by applying the event study methodology.

In the meantime, event studies have also been used in other contexts outside of "classic" economic research questions with a wide variety of investigative goals; for example, a study from the field of biotechnology dealt with the effect of patent applications on the value of rival firms (Austin, 1993). Other studies examined the effect of football match victories on the value of the winning teams' respective major sponsors (Benkraiem & Louhichi, 2009; Scholtens & Peenstra, 2009) or the impact of IT outsourcing (Duan *et al.*, 2009) and IT failures (Goel & Shawky, 2009).

Event studies are based on several classical financial theories and also serve to test specific theoretical finance concepts. The question of why certain events cause short-term reactions in capital markets is closely linked to main capital market theories, such as the principle of the rationality of market participants (as a central characteristic of *Homo Oeconomicus* and a basic assumption of the efficient market hypothesis), which has been described in Chapter 2 and which is, in particular, central to the event study methodology. When new information is published, investors are expected to process this information and price it into the share price without delay. The financial impact of new information can, therefore, be determined by measuring the change in share prices (Wang & Ngai, 2020). This change in the capital of shares thus represents the changed expectations of market participants based on the new information (Wang & Ngai, 2020).

Assuming the strong form of market efficiency, all observations should be fully explainable by a rational inclusion of the available information by the market participants. However, the principal-agent theory, as a fundamental principle of asymmetric information distribution and the concept of information efficiency, already implies that information is not always fully available to all market participants, pointing to disturbances in market efficiency. Apart from testing market efficiency, the event study also makes it possible to measure (sentiment-driven) effects that classical economic theories cannot explain. These effects may also exist during “normal times” but may be further amplified by the occurrence of unexpected events, such as exogenous shocks, and due to the uncertainty they induce in the market. As shown in previous investigations, uncertainty and risk increase the role and impact of (irrational) sentiment compared to other situations (Kim *et al.*, 2021; Lee & Ryu, 2024).

4.4.2 Structure of the Event Study

This section describes the procedure for conducting an event study in more detail. The structured procedure of an event study is described differently by different authors. In addition, since the 1980s, there has been a parallel strand of research that deals with the theoretical-statistical or econometric framework of the event study as a method. Detailed considerations were developed, for example, by McWilliams and Siegel (1997) and Kothari and Warner (2007). McWilliams and Siegel, for instance, propose a ten-step approach with a strong focus on the quality of the event study design. Extracts from their study will also be described in the following sections. Newer literature reviews summarizing the most recent developments in event study design have been published by Wang and Ngai (2020), Eden *et al.* (2022) and El Ghoul *et al.* (2023).

First, it needs to be noted that the different steps of the event study described below offer scope for adaptation to the individual situation under investigation. At the same time, the event study is subject to comparatively strict application requirements, which may lead to incorrect or less accurate results if violated. As an event study's success largely depends on the design of the event study framework, it is essential to define some basic assumptions and check the most critical parameters before conducting an event study (Brown & Warner, 1980; Brown & Warner, 1985; Pauser, 2008; Eden *et al.*, 2022). Before even starting, McWilliams and Siegel (1997) suggest checking whether the use of the event study methodology is appropriate in the research context. According to them, an event study needs to (1) have a financial impact, (2) be as non-anticipated as possible by the market participant, and (3) provide new information to the market (McWilliams & Siegel, 1997).

Furthermore, McWilliams and Siegel describe three basic assumptions on which every event study is based:

1. Markets are efficient
2. The event was not anticipated in advance
3. There were no other influencing events during the event period

In addition, they describe five essential research design and implementation issues (McWilliams & Siegel, 1997):

1. Sample size
2. Nonparametric test to identify outliers

3. The length of the event window and its justification
4. Confounding events
5. Explanation of the abnormal returns

Having defined the assumptions and essential research and implementation issues, the ideal-typical procedure of an event study may be discussed. For instance, several recent studies investigating investors' reaction to events refer to an approach by MacKinlay (1997) (Flammer, 2013; Ichev & Marinč, 2018; Goodell & Huynh, 2020) as a basis for their event study. MacKinlay (1997) describes the following steps to conduct an event study:

1. Defining the event of interest and the length of the event window
2. Determination of the selection criteria for the sample
3. Definition of the observation window, calculation of normal returns and abnormal returns
4. Design of the abnormal returns testing framework: Formulation of the hypothesis and calculation of the CARs.
5. Presentation of diagnostics and empirical results

In the following sections, the steps for conducting an event study based on the mentioned stages are explained in more detail. The formulation of the hypotheses has already been described in more detail in Chapter 3 and is therefore not described separately.

Defining the Event to be Observed: Event Time and Event Window

In general, the period of the event window should be selected carefully depending on its usefulness concerning the research question (MacKinlay, 1997), taking into account some factors that can impact the quality of the event study (Eden *et al.*, 2022; Blajer-Gołębiewska & Nowak, 2024). There is no "standard window" that suits every event study design and research purpose (Eden *et al.*, 2022). In principle, the literature distinguishes between "long horizon studies" and "short horizon studies", each using shorter or longer investigation periods. This distinction is not dogmatic but merely a point of reference and orientation. It is generally assumed that studies with an investigation period of longer than one year are to be assigned to the "long horizon" (Kothari & Warner, 2007). As a rule, the use of short-horizon studies is recommended, since the longer the survey, the greater the probability of the occurrence of other variables that influence stock prices (Curran & Moran, 2007). Lyon, Barber, and Tsai even described the long-horizon study as "treacherous" (Lyon, Barber & Tsai, 1999). Brown and Warner found that long event windows reduce the test statistic's power (Brown & Warner, 1980; Brown & Warner, 1985). As stated by McWilliams & Siegel, the event window should be as short as possible while still capturing the "effect" of the event (McWilliams & Siegel, 1997; Eden *et al.*, 2022).

For short-horizon studies, an event period of several trading days is the most frequently chosen length. McWilliams and Siegel argue that it has already been empirically proven that a short event window is suitable to measure the impact of an event (McWilliams & Siegel, 1997). Less frequently, so-called intra-day studies record price data within one trading day (e.g., Będowska-Sójka, 2016). However, these are rarely encountered, firstly due to data availability and secondly due to the difficulty of scheduling the event to be observed to the minute (Gerpott, 2009). MacKinlay recommends including at least one trading day after the day the actual event occurs to measure the effects after the market has closed (MacKinlay, 1997).

Concerning the definition of the event to be observed, it is of central importance, particularly for excluding possible disturbance variables, to precisely determine the exact event time (Bowman, 1983; Pauser, 2008; Eden *et al.*, 2022). The decisive question is not when the event actually took place (effective day), but when the information reached the market participants (announcement day) (Eden *et al.*, 2022). This can be particularly relevant in international research contexts, as information sometimes only reaches markets with a delay due to time differences. Eden *et al.* (2022) cite the death of a political leader as an example. The relevant event here is not the date of death itself, but the time of the corresponding announcement. Further studies investigated the impact of the inclusion of a company to a specific stock market index, for both the announcement day and the effective day of inclusion (Cheung & Roca, 2013; Blajer-Gołębiewska & Nowak, 2024). In the case of companies listed in the US, for example, the time of publication of information in the Wall Street Journal or, since the introduction, the time of publication of ad hoc announcements (Hauser and Hauser, 2003) is often used as the event time for endogenous events (Thompson, 1995).

Certain events, such as an exogenous shock (in the present investigation in the form of individual events as part of a pandemic), can already be in the offing over a more extended period. On the one hand, new information can either be leaked before the actual announcement or people already react more sensitively to smaller pieces of information. On the other hand, an event can have an impact over a longer period after the event time. So, it can be useful to also measure the abnormal returns for some time prior to the announcement to check for leakage of information or anticipatory effects (McWilliams & Siegel, 1997; Clougherty & Duso, 2011; Tischer & Hildebrandt, 2014; Eden *et al.*, 2022). In addition, in some research contexts, it can be useful to observe the reactions to the event over a longer observation period after the event and not only in a short period right after. The use of symmetrical event windows, which cover both a period immediately before the event date, the event date itself, and a period of equal length after the event date, can provide corresponding insights in these cases (Çıtak, Akel & Ersoy, 2018; Blajer-Gołębiewska & Nowak, 2024).

Also, in case of an exogenous shock with sudden market reactions driven by sentiment, the time frame has to be kept short enough to isolate the desired observation. The longer an event window is selected, the more difficult it becomes to view the desired event and its effects in isolation (McWilliams & Siegel, 1997), resulting in more exclusions of observations in the sample due to confounding events in the event period for longer event windows (the role of confounding events will be discussed in the following section). Consequently, there is a trade-off between the event-window length and the sample size. McWilliams and Siegel describe the length of the event window and its justification as a "critical issue" for the successful design of an event study (McWilliams & Siegel, 1997).

Selection of Inclusion Criteria for the Companies

Studies often cover companies in a specific stock index or listed on a particular trading venue. When defining the sample, it is essential to define the overarching context of the sample, i.e., to identify connecting elements and precisely define the desired sample size (McWilliams & Siegel, 1997). In practice, this allocation is usually based on the affiliation of companies to a specific index or on the listing in a specific country. However, it can also be based on any other criteria.

In the next step, it is also essential to analyze the sample regarding the specific point in time to be observed. This involves eliminating observations affected by other factors ("confounding events"), which might distort a precise observation of the desired effect at that particular time. Examples of such confounding events are a substantial change to the company structure (McWilliams & Siegel, 1997), a change of a board member (Modi *et al.*, 2015), announcements of financial reports (Doh *et al.*, 2010; Modi *et al.*, 2015) or the announcement of a merger or an acquisition (McWilliams & Siegel, 1997; Modi *et al.*, 2015). Which events are ultimately seen as "confounding" depends on the hypothesis or theory that is being tested (Foster, 1980). This targeted exclusion of individual elements from the sample should be based on clear, comprehensible, and uniform criteria (McWilliams & Siegel, 1997) to avoid selection biases (Foster, 1980; Blajer-Gołębiewska & Nowak, 2024).

Foster (1980) suggests conducting an "information release analysis" for the considered companies, taking into account relevant sources such as newspapers or official reporting channels such as the Dialog Information Retrieval Service of the SEC and then either exclude companies in cases which are non to have caused problems in past research or to check for events which "appear to be related to differences in the observed security return" (Foster, 1980).

Foster also proposes several methods to handle the issue of confounding events. The author suggests either eliminating companies from the sample where confounding events have been identified, grouping companies that have been affected by the same confounding event, eliminating companies from the sample only for the "appropriate" period where the confounding event occurred, or just recalculating abnormal returns by subtracting the effect of the event (Foster, 1980). As a last alternative, Foster suggests keeping every company in the sample and just assuming that the impacts of possible confounding events are not relevant, as was done, for example, by Ball & Brown (1968).

Definition of the Observation Window, Calculation of Normal Returns, and Abnormal Returns

The estimation (or observation) window is a reference period in the event study. The expected return without any influence of confounding events is called a "normal return" or "expected return", while the difference between the actual ex-post return of a stock after the specific event is called the "abnormal return" (MacKinlay, 1997). In order to measure abnormal returns, expected normal returns must be determined using a comparison period (i.e., estimation window).

The term "estimation window" thus refers to the period during which the expected "normal" returns can be determined by averaging. A stable period should be used in which there were no economic events that could, in turn, cause "abnormal" returns. Accordingly, the event considered in the study is not included in the estimation period. As a rule, the estimation window is set before the actual event date. Exceptions are possible if company-internal or external (i.e. macroeconomic) variables have been changed between the pre-event (estimation) period and the event itself, making it difficult to determine normal returns meaningfully (Masulis, 1980). In this case, a time window after the event can also be selected, although this should not immediately follow the event window in order to rule out possible confounding effects (El Ghoul *et al.*, 2023).

In principle, a sufficiently long period should be selected to ensure that distortions from inherent events in the sample elements are avoided and that no significant macroeconomic changes occur that could affect the formation of the "normal returns." In this context, Krivin *et al.* found that, in many cases, shorter estimation/ observation windows can increase the power of the event study (Krivin *et al.*, 2003).

The lengths of observation windows chosen in the research range from a few trading days to years (Krivin *et al.*, 2003). For studies investigating daily stock returns, estimation windows of at least 100 days are common (El Ghoul *et al.*, 2023). The specific procedure for collecting the required data depends on the specific object of investigation. Usually, stock market data is gathered from reliable sources, usually from websites providing information on individual stock price development. Furthermore, there are several approaches to calculating “normal returns” and abnormal returns, which are going to be described in Chapters 4.5.4 and 4.5.5. A schematic overview of the time windows in event studies is presented in Figure 6.

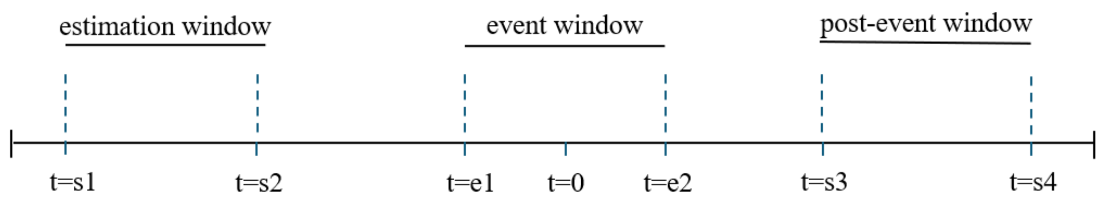

Figure 6. Schematic Representation of the Time Windows in the Event Study

Source: own compilation based on MacKinlay (1997).

4.4.3 Methods for Calculation and Normalization of Expected Returns

In order to divide the calculated returns of individual companies (or of an aggregated portfolio) into an expected “normal” return and an abnormal return as sharply as possible, a benchmark is needed that provides information on the return to be expected by the market (El Ghoul *et al.*, 2023). Several calculation models have been established, which are described by MacKinlay (1997) and El Ghoul *et al.* (2023), among others, and which will be briefly discussed below. The different models have been developed for various purposes, underlying various assumptions and prerequisites. A general distinction can be made between factorless, single-factor, and multi-factor models (Pauser, 2008). While the factorless models are limited to the purely statistical observation of the historical price development of the observed security, the single-factor or multi-factor models include additional factors that take certain disturbance variables into account from the outset and are thus intended to increase the quality of the abnormal return determined (Pauser, 2008). In line with this distinction, Brown and Warner (1980) distinguish between mean-adjusted return, market-adjusted return, and market- and risk-adjusted return models. The selection of the most suitable model is again decisive for the quality of the results obtained and dependent on the research goal. No model is superior to the other models in all contexts. Dyckman *et al.* (1984) applied multiple models to compare their results and thus further increase the quality of the study, indicating that the market model may be a more powerful test in comparison to the mean-adjusted returns model and the market-adjusted returns model. A selection of the most common models used in recent studies is briefly described below.

The Constant Mean Return Model

The Constant Mean Return Model, as a factorless model, is based only on an expected return and an expected disturbance variable. This model does not consider other securities (factors) and is based only on the mean returns of the company under investigation (Brown & Warner, 1980). While making it independent of sector—or market-dependent price movements, it also impedes the clear distinction between "expected" and "abnormal" returns since normalization is only carried out through a temporal, historical observation, and no additional current benchmark with comparable values is used. The idea of determining the expected return of a company based on its mean historical return goes back to Markowitz (1952) and his concept of Portfolio Selection.

The Market Model

The market model, as a single-factor model, takes into account, in addition to the historical mean returns of the company under consideration, the price change of a comparative portfolio, whereby in many cases, a broad-based market index such as the S&P 500 index is used for this purpose (MacKinlay, 1997). This consideration is based on the assumption that the return of an individual security is linearly related to the return of a sensibly selected market portfolio (Copeland, Weston & Shastri, 2005). The basic equation for calculating the market model is

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + e_{i,t}.$$

The total return $R_{i,t}$ is composed of the unsystematic return α_i, that a company can achieve from regular business activity, while the development of returns on the capital market $R_{m,t}$ is additionally weighted by employing the parameter β_i based on the dependence of the individual security return on the overall market return. Finally, $e_{i,t}$ represents an additional, unspecified, or specifiable disturbance variable (such as firm-specific factors that affect the security's return but are not captured by the market return). The two parameters β_i and α_i can be estimated via, i.e., the Ordinary Least Squares method of estimation (OLS) (Gerpott, 2009).

The market model thus represents an extension of the Constant Mean Return Model, as it considers the company-independent, market-dependent fluctuations to determine the abnormal returns. The market model is often applied in event studies because it offers good predictive power and pragmatic applicability (Brenner, 1979).

The Capital Asset Pricing Model

Other approaches, such as the Capital Asset Pricing Model (CAPM), developed by Sharpe (1963; 1964), Lintner (1965), and Mossin (1966), highlight the tradeoff between the risk of an asset and its expected return in addition to the pure consideration of the historical price development of the asset (Rossi, 2016). In the case of CAPM, the market model, as presented above, is extended by weighting the expected return of a company's security with its systematic risk relative to a market portfolio (Rossi, 2016).

In CAPM, the expected return is calculated with the following formula (Sharpe, 1964):

$$E(r_{i,t}) = R_f + \beta_i \cdot (E(R_{m,t}) - r_f)$$

with

R_f – risk-free interest rate at time t,

$\beta_i = \frac{\sigma_{i,m}}{\sigma_m^2}$ – systematic risk of security j relative to the market portfolio,

$E(R_{m,t})$ – expected value of the return of the market portfolio.

The abnormal returns can be determined by subtracting the expected return from the actually observed returns:

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

A positive $AR_{i,t}$ indicates that the asset has performed better than expected by the CAPM, while a negative abnormal return indicates a poorer performance.

The CAPM, in particular, is criticized for its lack of empirical suitability. Including a risk-free interest rate to determine abnormal returns initially raises the question of how the risk-free interest rate is to be determined empirically. In practice, the risk-free rate, as the theoretical rate of return that an investor would expect on an investment with zero risk, is operationalized, e.g., via the return of government bonds from countries with high credit ratings, which are considered as investments with a default risk close to zero (Seok *et al.*, 2019b).

Two empirical studies by Cable and Holland (1999a, 1999b) certify the superiority of the market model over the CAPM in almost all cases examined. In another study by French (2018), no differences were found between the use of the statistical mean and the CAPM. In response to the apparent weaknesses, Fama and French initially developed their 3-factor model (1992), which supplements the CAPM by adding the excess return of a small stock portfolio in comparison to a portfolio containing large stocks (size premium) and the excess return of a portfolio with a high book-to-market value in comparison to a portfolio with a low book-to-market value (value premium) (Fama & French, 1992). Later, they extended their model by introducing a five-factor model (Fama & French, 2015), where two other factors were added: profitability and investment premiums.

4.4.4 Abnormal Returns and Cumulative Abnormal Returns: Calculation and Testing Framework

The event study focuses on determining abnormal returns resulting from securities price changes. Therefore, the change in the shareholder value of securities is the object of observation.

In general, the returns for a security i under consideration at the time t can be determined as (Kothari & Warner, 2007; El Ghoul *et al.*, 2023):

$$R_{i,t} = E\left(R_{i,t} \middle| \Omega_t\right) + AR_{i,t}$$

where Ω_t denotes the information set in the observation window, $E\left(R_{i,t} \middle| \Omega_t\right)$ denotes the expected normal returns and $AR_{i,t}$ the "abnormal returns" for a company i at time t, which results in a deviation from the expected normal return as a consequence of the event under consideration. When using the market model, abnormal returns are considered to be the disturbing portion of the calculation (MacKinlay, 1997). This means that $AR_{i,t}$ denotes the abnormal returns, consequently resulting from the difference between the actual returns $R_{i,t}$ and the expected returns $E(R_{i,t}|\Omega_t)$ determined from the estimation period. The general formula for calculating the "abnormal" returns is thus:

$$AR_{i,t} = R_{i,t} - E(R|\Omega_t).$$

The expected returns are subtracted to isolate abnormal returns resulting from the event and decouple them from price changes induced by general market movements (Pauser, 2008). A complete and immediate reinvestment is assumed if dividends are paid during the event period (Gerpott, 2009). In addition to examining individual companies, it is also possible, for example, to analyze the aggregated earnings of several companies operating in the same industry (Pauser, 2008).

Aggregating abnormal returns to cumulative abnormal returns, as in determining normal or abnormal returns, can be done in various ways (El Ghoul *et al.*, 2023). The concrete procedure must be selected based on the research objectives and the research design. The null hypothesis is usually taken as given in all event studies: The abnormal returns induced by a specific event correspond to 0. The further development of the hypothesis for the current study is described in Chapter 3 and will, therefore, not be addressed again in this section.

Several test procedures are suitable for testing the significance of the event study. The optimal test procedure depends on the sample and must, therefore, be derived individually. The subsequent sections will present several approaches to testing and evaluating the hypothesis, including prior testing of a fulfillment of the basic assumptions of specific test procedures. The evaluation and interpretation of the event study results round off the procedure.

Methods for the Calculation of CARs

Two methods have become established in the literature for summing up the (abnormal) returns in the context of event studies, also over a multi-period view: the cumulative abnormal returns (CARs) or the buy and hold abnormal returns (BHARs) (Kothari & Warner, 2007; El Ghoul *et al.* 2023). The CARs can be aggregated either through time for individual securities or by summing up the abnormal returns of different companies (MacKinlay, 1997). The CARs are calculated based on the abnormal returns determined for each period by choosing the aggregation through time, as presented in the formula:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_t$$

In addition, the variance of the observations is usually determined and set in relation to the CARs in order to calibrate the observations. Depending on the observed event, there is always the risk that this will induce a higher variability of capital market prices due to a less clear view of the future of the company under consideration:

$$\frac{CAR(t_1, t_2)}{[\sigma^2(t_1, t_2)]^{\frac{1}{2}}}$$

with

$$\sigma^2(t_1, t_2) \quad = L\sigma^2(AR_t),$$

where $\sigma^2(AR_t)$ is the variance of the one-period average abnormal return. The equation thus underlines the statement of Lyon, Barber, and Tsai (1999), calling long-horizon studies "treacherous" due to the increasing variance with increasing time horizons. Event studies with short horizons, however, are considered "straightforward and relatively trouble-free" (Kothari & Warner, 2007).

4.4.5 Diagnostics and Statistical Tests

In his study (1997), MacKinlay emphasizes that the “presentation of diagnostics” is necessary because, in some event studies, the results “can be heavily influenced by one or two firms.” This clustering risk is only one aspect of thoroughly examining the statistical requirements for applying specific econometric test procedures. The applicability of statistical tests is always based on the fulfillment of particular prerequisites in the sample. Reliable and robust results depend on conducting preliminary tests to verify these prerequisites. Without them, test procedures may be invalid, and the risk of statistical error increases.

Checking the Statistical Assumptions and Robustness of the Surveyed Sample

All statistical procedures must fulfill specific quality criteria to minimize the risk of deviations (Gerson, 2012). These criteria vary by procedure and can be verified by applying tailored preliminary tests.

In the applied test procedures themselves, a distinction can be made between parametric and non-parametric test procedures (Gerson, 2012). As a rule, the requirements are higher for parametric procedures than for non-parametric procedures (Brown & Warner, 1980; Campbell *et al.*, 1993).

Parametric test procedures require, apart from a sufficiently large sample size, three fundamental assumptions to be fulfilled to produce reliable and valid results (Gerson, 2012):

- Independence of the observations (i.e., no autocorrelation in the sample)
- Homogeneity of variance
- Normal distribution of the data within the sample

Parametric tests are commonly used to assess the significance of study results (Gerson, 2012), but non-parametric tests offer an alternative when individual basic assumptions of the parametric test procedures are violated.

The following test procedures are suitable for testing the basic assumptions of parametric test procedures:

- Tests for independence of the observations

  Time series data, in particular, are prone to autocorrelation (Gerson, 2012), as a time series value at time $t + 1$ directly depends on the value level at the time t. The same applies to grouped data or data from repeated investigations. Event studies are, in particular, subject to cross-sectional correlation due to the use of time series data and the observation of the same event times for the items in the sample, potentially causing "over-rejection" of the null hypothesis (Kolari & Pynnönen, 2010). The Durbin-Watson test is a frequently used option for detecting autocorrelation (Gerson, 2012).

- Tests for homogeneity of variance

  The homogeneity of the sample's variances is crucial when analyzing variance (Gerson, 2012). Levene's test of homogeneity of variance (Gerson, 2012) is commonly used, while other procedures such as the Brown and Forsyth test, Welch test, or Bartlett's test are used in particular test variations (Gerson, 2012).

- Tests for normality of the distribution

  Several procedures are used to test the normality of the distribution. Apart from a visual inspection of the sample's distribution (Gerson, 2012), the Doornik-Hansen test is an easy-to-use test of the sample for normality based on skewness and kurtosis measurements (Doornik & Hansen, 2008), while the Shapiro-Wilk test analyzes the sample based on an analysis of variance (Shapiro & Wilk, 1965). It is one of the most frequently used test procedures for testing normality based on the empirical distribution function (EDF) (Das & Imon, 2016). The Lilliefors test (a Kolmogorov-Smirnov test variant) is also a well-known and widely used test for testing normality (Lilliefors, 1967; Abdi & Molin, 2007). Lastly, the Jarque–Bera test is a procedure based on descriptive measures (Thadewald & Büning, 2007; Das & Imon, 2016).

Concerning the event study, there are various problems with the application of parametric test procedures. Due to the frequent use of time series data in event studies, the data used is autocorrelated in many cases. In addition, Brown & Warner (1980) already argued that the variance is increased by the event itself, increasing, in turn, the susceptibility to parametric test error. A normal sample distribution is also often not given, as the data collected no longer has a linear relationship due to the influence of the event under investigation. In many cases, non-parametric test procedures must therefore be used.

Significance Tests

The results of an event study are empirically validated through statistical significance tests at a defined significance level. Ultimately, the aim is to limit the error probability to a certain level (e.g., 5% or 1%) when transferring the results to the population. Various test procedures have been established for this purpose. After checking the statistical assumptions, a suitable parametric or non-parametric test procedure is selected.

Both parametric and non-parametric procedures have advantages and disadvantages. Non-parametric procedures are generally considered more robust, leading to a valid and reliable result in more samples (Gerson, 2012). Parametric procedures, in turn, have a higher test strength. A parametric procedure would provide a more accurate result with the same sample than a non-parametric test procedure (when assumptions are fulfilled) (Gerson, 2012). Therefore, parametric test procedures are always preferred if no basic assumptions of these procedures are violated (MacKinlay, 1997). Carrying out the significance test with both a parametric and a non-parametric procedure can be helpful to avoid falsely rejecting or accepting the null hypothesis. In this case, an unambiguous statement concerning the hypothesis can only be made if both tests arrive at the same result.

In the following section, examples of the t-test as a parametric procedure, as well as the Generalized Sign Test and the Mann-Whitney (U) Test as nonparametric procedures, are discussed. The Generalized Sign Test is often used in event studies (Serra, 2004) and will be applied in the dissertation. The Mann-Whitney U Test is a nonparametric test procedure used to compare groups from the same sample (Nachar, 2008).

The t-test – a parametric Significance Test

The t-test, as a frequently chosen statistical significance test—also in the context of significance testing of event studies—is defined by:

$$\mathrm{t} = \frac{\overline{\mathrm{AR_t}}}{\mathrm{s}(\overline{\mathrm{AR_t}})}.$$

Thus, the observed average abnormal return $\overline{AR_t}$ in the event window is divided by the measured average standard deviation in the estimation period. The standard deviation $s(\overline{AR_t})$ is determined as follows, taking into account the determined average abnormal returns:

$$s(\overline{AR_t}) = \left[\sum_{t=1}^{T} (\overline{AR_t} - \overline{\overline{AR}})^2 \, (T-1)^{-1}\right]^{0,5}$$

where t represents the respective trading day of the estimation period, while T is the last day of the period. The term $\overline{\overline{AR}}$ denotes the mean value of the average abnormal returns.

To test the significance, the t-value determined in this way is compared with the theoretical t-value with a given number of degrees of freedom (in this case, the number of degrees of freedom results from the number of trading days in the estimation period, reduced by 1). If the empirically determined value exceeds the theoretical value, the null hypothesis must be rejected accordingly (Gerpott, 2009).

The Generalized Sign Z test – a non-parametric Significance Test

Before the Generalized Sign Test or Generalized Sign Z became a popular significance test for event studies, the Sign Test by Brown and Warner (1980) was often used (Cowan, 1992). According to Cowan (1992), the main weakness of applying the Sign Test for significance testing is the necessary distribution of 50% positive abnormal returns to 50% negative abnormal returns without the influence of a specific event. The test is based on comparing the distribution in the event window with an assumed uniform distribution at another point in time without influencing events. As this assumption is often violated in empirical applications, the power of the test procedure is partially limited (Cowan, 1992). The Generalized Sign Test, first applied by Cowan, Nayar, and Singh (1990) and Sanger and Peterson (1990), solves this problem by comparing the distribution between positive and negative abnormal returns in the event window with the actual distribution at another, unaffected point in time, a symmetric distribution of the cross-sectional abnormal returns is thus no longer necessary (Cowan, 1992). Apart from this, an empirical comparison of the procedure with, for example, the rank test by Corrado as an alternative, non-parametric test procedure shows that the Generalized Sign Test becomes relatively more robust with increasing length of the event windows. While the Rank Test has greater power for event windows of one or two trading days, the Generalized Sign Test delivers more reliable results for longer windows (Cowan, 1992).

To calculate the Generalized Sign Test, the comparative value of the positive cumulative abnormal returns in a period without external influence must first be calculated, with which the CARs in the event window are then compared. The comparison value is calculated using the following formula (Cowan, 1992):

$$\hat{p} = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{100}\sum_{t=E_1}^{E_{100}} S_{jt}$$

with

$$\mathrm{S_{jt}} = \begin{cases} 1, \text{if } \mathrm{AR_{jt}} > 0 \\ 0, \text{otherwise} \end{cases}.$$

The test statistic of the generalized sign test is calculated using the formula (Cowan, 1992)

$$Z_G = \frac{\omega - n\hat{p}}{[n\hat{p}(1-\hat{p})]^{\frac{1}{2}}}$$

with ω as the number of stocks with positive CARs during the event window, and n stands for the sample size.

The Mann-Whitney U test – a non-parametric Significance Test

The Mann-Whitney U test (Mann & Whitney, 1947) is another non-parametric test procedure suitable for analyzing the differences between two data sets with an ordinal data structure (MacFarland & Yates, 2016), being reliable even with small, non-normally distributed samples. It is often used as a non-parametric counterpart to the parametric Student's t-test (Nachar, 2008). The H_0 hypothesis of the Mann-Whitney U test assumes that two groups with n observations are part of the same population and therefore show no significant differences in their distribution.

To test the H_0 hypothesis, it is necessary to calculate a U-statistic for each group, the distribution of which is known based on the null hypothesis and was documented in tables by Mann and Whitney (1947). The U statistics for each group are defined in two formulas (Nachar, 2008):

$$Ux = nxny + \left(\frac{nx(nx+1)}{2}\right) - Rx$$

and

$$Uy = nxny + \left(\frac{ny(ny+1)}{2}\right) - Ry$$

with nx of the number of observations in the first group and ny as the number of observations of the second group, Rx and Ry are the sum of the ranks assigned to the first and to the second group (Nachar, 2008).

For samples with more than 8 observations (as the distribution of the sample approaches a normal distribution, which is the applicable case in the current dissertation), the following formula can be used to calculate the test statistic:

$$\mu_u = \frac{nxny}{2} = (Ux + Uy)2$$

and

$$\sigma_u = \sqrt{((nxny)(N+1))/12}$$

with $N = (nx + ny)$ and μ_u / σ_u referring to the average and the standard deviation of the U distribution.

The advantages of the Mann-Whitney U test lie in its broad applicability, even if the sample is not normally distributed or if the sample size is small. According to Nachar (2008), Landers (1981) found the statistical power of the test procedure to be comparatively high, reaching 95% of the power of the parametric Student's t-test for an average sample size greater than 10. Apart from this, the test procedure's only relevant disadvantage lies in the fact that, as mentioned earlier, the procedure does not quite achieve the power of the comparable t-test. As with other comparisons between parametric and non-parametric test procedures, the t-test should always be used before the Mann-Whitney U test if the basic assumptions for using the parametric test procedure are fulfilled (Nachar, 2008). Nachar (2008) summarizes that the Mann-Whitney U Test is an “excellent alternative to parametric tests”.

As described comprehensively in Chapter 4.4, an event study can be carried out using different methodological approaches. In the present study, the security prices of individual companies are examined. It is, therefore, useful to use market-oriented methods to calculate the event study as well. For this reason, the normal returns are calculated based on the market model, and the ARs and CARs are aggregated using the definitions and formulas presented in the respective section. As furthermore shown in section 4.5.3, the selection of the estimation window, event date, and event window, and a thorough selection of the companies to be included in the sample are essential for the quality of the test results. A special focus should therefore be placed on the derivation of these elements as part of the research design. As will be shown in section 5.2.3, using the specific sample and applying the test procedures described in section 4.5.7, the sample violates the basic assumptions of the t-test, which is why this parametric test procedure cannot be used for the significance test. The nonparametric procedure used to test the hypotheses is derived and described separately in the various subsections.

4.5 Volatility Analysis in the Wake of Exogenous Shocks

The following section outlines procedures to analyze the volatility development after exogenous shocks, as addressed in hypotheses H3a, H3b, and H3c related to Research Question 6 (RQ6). In this dissertation, volatility is defined, based on a definition of Balaban *et al.* (2006), as the daily standard deviation of continuously compounded daily returns.

The calculation or investigation of stock price volatility after an exogenous shock differs fundamentally from the investigation of, for example, price developments as described in the previous sections. Traditional event studies assume constant volatility (Brown & Warner, 1980; Corrado, 1989), which is often not the case in practice. However, Brown & Warner (1980) make clear that increases in variance following an event may lead to misspecifications and a reduction in the power of the test statistic. Furthermore, financial time series also frequently show strong (unconditional) heteroscedasticity (Balaban & Constantinou, 2006). When conducting an event study, using the conditional volatility model, which, according to Balaban & Constantinou (2006), provides accurate out-of-sample forecasts of financial asset returns, can help to overcome these limitations. In 2006, Balaban and Constantinou developed, following an initial research proposal by Savickas (2003), a new approach based on a GARCH model to test the impact of an event on the mean and conditional volatility function of share returns for the investigated companies. The approach will be described in the following section.

4.5.1 GARCH Models

To calculate abnormal behavior in the stock prices' volatility, a GARCH model approach can first be applied at the individual company level and based on comparable studies (Białkowski *et al.*, 2008; Tweneboah-Koduah *et al.*, 2020) to determine the "normal" volatility on the event days under consideration. GARCH models are particularly suitable for investigating stock price volatility (Franses & Van Dijk, 1996; Chong *et al.*, 1999). The approach has been developed further over the years, introducing various calculation approaches (Bauwens *et al.*, 2006). Autoregressive moving average (ARMA) models were initially used to analyze volatility to examine a sample's mean more closely (Bauwens *et al.*, 2006). Since the 1980s, volatility analysis has increasingly focused on Autoregressive Conditional Heteroscedasticity (ARCH) models, first developed and introduced by Engle (1982). While ARMA models assume variance to be constant over time, ARCH models predict volatility by considering the variance of the error terms in a time series model as conditionally heteroscedastic (Engle, 1982) or, in other words, allowing "the conditional variance to change over time as a function of past errors, leaving the unconditional variance constant" (Bollerslev, 1986). In 1986, Bollerslev developed the ARCH-model approach into the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. As the conditional variance was generated as a linear function of the past errors in the ARCH approach, a long lag in the equation of the conditional variance was often required in studies. The GARCH model extends the already empirically tested ARCH approach to include the possibility of integrating lagging conditional variance in a more flexible approach or "adaptive learning mechanism" (Bollerslev, 1986). The model is, therefore, better able to capture the persistence of volatility (Bollerslev, 1986). In 2022, Lúcio and Caiado (2022) state that the impact of COVID-19 on stock volatility has not yet been analyzed in an aggregated approach and that state-of-the-art methodologies do not offer such possibilities. Consequently, they use a new model clustering method based on a fitted TGARCH model to analyze sectoral impacts on volatility for the S&P 500 index and in the context of the COVID-19 outbreak.

The basic model applied in this dissertation is based on two formulas, which have been extended in an approach by Balaban and Constantinou (2006), focused on analyzing event-induced volatility after mergers and acquisitions among UK companies:

$$R_{i,t} = c_i + \beta_i \cdot R_{m,t} + \gamma_i \cdot D_{i,t} + \varepsilon_{i,t}$$

$$h^2{}_{i,t} = \alpha_{i,0} + \alpha_{i,1} \cdot \varepsilon^2{}_{i,t-1} + \lambda_i \cdot h^2{}_{i,t-1} + \delta_i \cdot D_{i,t},$$

where $R_{i,t}$ is a firm-specific return for a company i at time t and $R_{m,t}$ is the return of the whole market (e.g., the S&P 500 index) at time t. The dummy-variable $D_{i,t} = 1$ at the time of the event and $D_{i,t} = 0$ for all other points in time for a company i. Parameters γ_i and δ_i determine respectively the abnormal returns and the abnormal or event-induced volatility for the company i (Balaban & Constantinou, 2006).

Variable ${h^2}_{i,t}$ denotes the variance of the time series for a company i at time t, while ${h^2}_{i,,t-1}$ denotes the variance of the previous period. The parameters $\alpha_{i,0}$, $\alpha_{i,1}$ and λ_i need to be estimated (Balaban & Constantinou, 2006).

4.5.2 Testing the Significance of the GARCH Model

The GARCH model's results can be tested for significance using an approach proposed by Savickas (2003), which was extended by Balaban and Constantinou (2006).

Starting from calculating a typical and widely-used cross-sectional test statistic, which is often applied to analyze price volatility in event study frameworks and which uses the $\boldsymbol{\gamma}$ determined in the GARCH calculation as a central element of the test statistic $(test_1)$ (Brown & Warner, 1980), the authors, in an extended approach $(test_2)$, standardize the determined values for $\boldsymbol{\gamma}$ using the estimated conditional standard deviation $\hat{h}_{i,t}$ of a company i'th stock prices at the respective event time (Balaban & Constantinou, 2006). The extended version of the test was employed in our study, since the original approach of Brown and Warner (1980) assumes a uniform unconditional standard deviation of companies' prices in the sample, which is not useful in the context of Research Question 6 (RQ6) and with a focus on company-specific effects (Tweneboah-Koduah *et al.*, 2020). The extended approach by Balaban and Constantinou (2006) includes the company-specific, estimated conditional standard deviation on the respective event date to ensure the company-specific view on the one hand and the event-induced effects on the other hand. Furthermore, the occurrence of "abnormal" stock price volatility can be determined holistically based on the entire sample and time series and, therefore, does not depend on a specific selection of an event period by the researcher (Balaban & Constantinou, 2006).

To summarize, $test_2$ addresses whether "abnormal" volatility occurred in the course of an event and takes into account the company-specific conditional standard deviation on the day of the event, while $test_1$ does not take this factor into account:

$$test_1(\hat{\gamma}) = \left\{\sum_{i=1}^{n} \frac{\hat{\gamma}_i}{n}\right\} / \left\{[1/n(n-1)] \sum_{i=1}^{n} \left[\hat{\gamma}_i - \sum_{i=1}^{n} \frac{\hat{\gamma}_i}{n}\right]^2\right\}^{0,5},$$

$$test_2(\hat{\gamma}) = \left\{\sum_{i=1}^{n} \frac{S_{i,t}}{n}\right\} / \left\{[1/n(n-1)] \sum_{i=1}^{n} \left[S_{i,t} - \sum_{j=1}^{n} \frac{S_{j,t}}{n}\right]^2\right\}^{0,5},$$

with $S_{i,t} = \frac{\hat{\gamma}_i}{\hat{h}_{i,t}}$.

The calculation results in a statement about significant deviations in volatility over the observation period for the individual companies compared to the observation period itself. According to the authors, their approach delivers significantly more reliable results than the typical GARCH model (Savickas, 2003; Balaban & Constantinou, 2006) and a cross-sectional test statistic. Therefore, even though the results of both significance tests are given in the current dissertation, the results of $test_2$ are regarded as decisive for testing Volatility Hypotheses (H3a, H3b, and H3c).

Chapter 4 outlined an overview of the methodologies and test procedures relevant to testing the hypotheses derived in Chapter 3. Thus, it provides a theoretical framework that forms the foundation for further exploration of the specific research context in this study. This contextualization is presented in Chapter 5.

CHAPTER 5
RESEARCH DESIGN AND DATA COLLECTION

Chapter 5 describes the specific procedure for collecting and calculating the relevant data for further hypothesis testing. Based on the econometric methods described in Chapter 4 and the derived methods to be used, the following section describes how the investigation of the hypothesis was prepared and conducted. The first section of Chapter 5 describes the calculation of the investor sentiment indicator (related to Stage 1 of the investigation). The second section of the chapter describes the research design and data collection process for the event study analysis based on investor sentiment indicators. The last two sections describe the methodology and specific calculation of the volatility analysis for the investigation of hypotheses H3a, H3b, and H3c, corresponding to Stage 3 of the investigation, as well as the procedure for measuring and investigating the role of company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices (Stage 4).

5.1 Calculation of the Sentiment Indicator

This subchapter describes the calculation of the investor sentiment indicator. As explained in the "Hypotheses Development" section (Chapter 3), the first stage of this study considers two dimensions of investor sentiment and their development over the period under review. Firstly, investor sentiment is calculated, analyzed, and compared at the company level. Secondly, individual results for companies are weighted and aggregated according to their sector affiliation. The calculated individual company sentiment is then used for further calculations.

5.1.1 Calculating the Daily, Company-Specific Sentiment Indicator

The foundations for calculating the company-specific investor sentiment are derived from the method proposed by Seok, Cho, and Ryu (2019b) based on four market indicators, which are individually related to investor sentiment: The Relative Strength Index ($RSI(14)$), the Psychological Line Index ($PLI(12)$), the Logarithm of Stock Turnover (LTV), and the Adjusted Turnover Rate (ATR).

The study sample comprises companies included in the S&P 500 index, representing various sectors. There are several classification systems, each of which distinguishes between a different number of sectors. The Global Industry Classification System (GICS) and the Industry Classification Benchmark (ICB) are the two best-known classification systems for assigning companies to predefined sectors and subsectors. While not being entirely consistent, the GICS was chosen in this study, as it is the standard for the S&P 500 index. The distribution of the companies between sectors is presented in Table 4.

Table 4. Allocation of Companies in the S&P 500 Index to Sectors According to GICS

GICS Sector	No. of Companies in S&P 500 Index
Communication Services	22
Consumer Discretionary	56
Consumer Staples	33
Energy	23
Financials	67
Health Care	64
Industrials	70
Information Technology	76
Materials	29
Real Estate	30
Utilities	30
Total	**500**

Source: own compilation.

In order to get a broad view of the development of the investor sentiment indicators, the calculation of the data is based on daily values for opening and closing prices of the securities examined for the period between January 2nd, 2019, and April 30th, 2020, which amounts to a total of 334 trading days. The relevant data was obtained from the Yahoo Finance website, which provides recognized and reliable stock price information. Furthermore, the daily trading volume was also obtained from Yahoo Finance. Information on outstanding shares obtained from various sources, such as company websites or annual reports, was therefore specified individually depending on the security under consideration.

Calculation of the Relative Strength Index (RSI(14))

To calculate the $RSI(14)$, the daily return of a security must first be determined and expressed in absolute terms in the underlying currency. For this purpose, the daily closing price of the previous day is subtracted from the daily closing price of the day under consideration. The

$RSI(14)$ is now calculated based on the definitions given in Chapter 4 for a length of 14 trading days.

The $RSI(14)$ values range from 0 to 100. If the divisor of absolute price gains and price losses results in 1, i.e., the absolute price gains and the absolute price losses are equal, the RSI according to the above calculation formula is 50, i.e., exactly the middle between the minimum and the maximum value, which means that the security is neither overbought nor oversold. The security is considered oversold for $RSI(14)$ between 0 and 49, while a value between 51 and 100 is considered overbought. Figure 7 shows a schematic representation of the different areas of the RSI and their corresponding "statement".

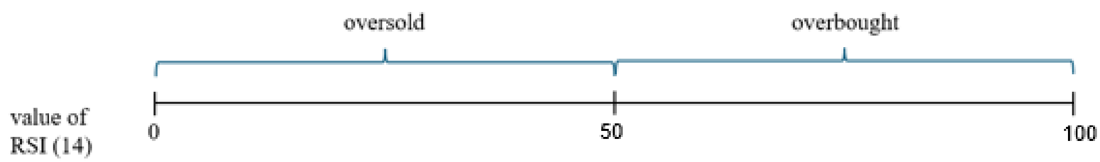

Figure 7. Areas and Statements of *RSI(14)*

Source: own compilation.

For the sample used in this study, the average $RSI(14)$ was determined to be 53.58, with the company Apple Inc. showing the highest arithmetic average of 61.89 and Paramount Global showing the lowest arithmetic average of 44.89 for the entire observation period.

Calculation of the Psychological Line Index (PLI(12))

The Psychological Line Index follows a similar logic and approach to the $RSI(14)$, whereby in the calculation, not the absolute price gains or losses per trading day are involved, but only the number of trading days with gains and the number of trading days with losses are put into relation. Thus, in contrast to the calculation logic of the $RSI(14)$, it is not decisive how strong the price movements per trading day ultimately turned out to be. Consequently, as already described in Chapter 4, the PLI can indicate an optimistic attitude towards a security, even if the security records price losses in absolute terms during the period under review (and vice versa).

In this study, the $PLI(12)$ can be derived from the closing prices, which are determined similarly to the $RSI(14)$. For this purpose, the difference between two consecutive closing prices is determined. The $PLI(12)$ ranges between 0 and 100. The average value for the companies included in the sample was 53.02. The highest average value for an individual company was 61.37 (Corpay Inc.), while the lowest average value for a company was 46.05 (GE Aerospace; formerly General Electric).

Calculation of the logarithm of the trading volume (LTV)

The trading volume can also be retrieved via Yahoo Finance, which is analogous to the data regarding the price developments of individual securities. The values retrieved there are then logarithmized using the standard calculation procedure as described in Chapter 4.

Apple Inc. had the highest average LTV of the sample with a value of 8.075, while NVR Inc. showed the lowest average value of 4.418.

Calculation of the adjusted turnover rate (ATR)

In contrast to the “simple” trading volume, the adjusted turnover rate indicates the proportion of the total available securities traded on a given trading day. This information is supplemented by the sign of the ratio, indicating whether a total price gain or loss was achieved on the respective trading day.

In addition to the data already required for calculating the other KPIs, the total number of shares issued ("outstanding shares") is required for calculating the ATR. The outstanding shares were determined individually for each company. So, it required research into each company’s annual reports, company websites, and general financial websites. The number of outstanding shares does not vary on a daily basis, as it changes, for example, due to the issuance of new shares or the repurchase of shares by the company (Nelson, 1999). Therefore, it is also possible that the number of outstanding shares remains constant over the entire calculation period. For the calculation, only a stock’s daily individual trading volume is set in relation to the outstanding shares according to the formula provided in Chapter 4.

The highest average ATR was observed for Advanced Micro Technologies (AMD), with a value of 0.006. The lowest average ATR was found for Ralph Lauren Corp. with an average ATR of -0.002.

5.1.2 Merging the Sub-Indicators to a Daily, Company-Specific Sentiment Indicator

As described in Chapter 4, the sub-indicators determined are adjusted for the return "of the market" in the next step. The challenge here is operationalizing a risk-free return in the context of the research question. Seok *et al.* (2015) focus on a selection of Korean companies and use the difference between the daily price development of the Korean KOSPI index, which broadly reflects the Korean market, and the 91-day deposit rate, which is considered comparatively risk-free. The difference between the two values represents the "market share" or market excess return, against which the individual components of the overall sentiment indicator can be regressed in the next step. A similar approach will be taken for this study. Since the firms considered in the current investigation are companies included in the S&P 500 index and assuming that country-specific factors also play a role in the price development, the analysis will be based on the S&P 500 index of the US. This approach is a simplifying assumption, as the companies under consideration do not operate exclusively in one market but, in many cases, globally. However, it is a common practice to make such a simplification. For instance, in the study of Korean companies mentioned above, they were also not exclusively active in the Korean market.

In line with this approach, for companies included on the S&P 500 index, the difference between the return of the total S&P 500 index return itself as a recognized and broad index of large US companies and the return of US 10-year government bonds is calculated as the market excess return:

$$Market\ excess\ return = R_m - R_f$$

with R_m as the market returns and R_f as the risk-free return rate. US government bonds are said to have an excellent credit rating and only a minimal default risk, so the return on this financial instrument can be assumed "risk-free".

The final calculation of the daily, company-specific sentiment indicators is then based on the steps described in Chapter 4. After the different sub-indicators are regressed against the market excess return, a principal component analysis is conducted using the residuals of the regressions. Finally, the calculated principal components are appropriately used to create the final sentiment indicator.

5.1.3 Calculation of the Overall Sentiment Indicator and Sectoral Sentiment Indicators

Research Question 4 (RQ4) deals with whether a market-based approach to measuring sentiment is a reliable predictor of future security performance. This question is to be answered for the daily returns of the S&P 500 index, which is why investor sentiment must first be determined at the aggregated level of the S&P 500 Index. Chapter 5.1 describes in detail the calculation of the daily company-specific sentiment indicators. These are added to construct the aggregated sentiment indicator, referred to below as the Overall Sentiment Indicator (OSI). A weighting is applied based on the market capitalization of the respective company for the addition. This corresponds to the logic behind the formation of the S&P 500 Index (Chapter 2.6), which also includes share price performance based on a weighting of market capitalization:

$$OSI_t = \sum_{i=1}^{k} \frac{MC_i}{MC_S} \times SI_{i,t}$$

with MC_i as the market capitalization of a company i, MC_S as the sum of the market capitalizations of the companies in the sample and $SI_{i,t}$ as the sentiment indicator value of a company i at time t.

A sector-specific analysis offers the advantage that apparent differences between the sectors can be identified and thus considered in the research design if necessary. According to Foster (1980), pairing companies from the same sectors may be necessary to avoid errors in the research design. For simplification, the present study does not include a statistical significance test, e.g., for the occurrence of abnormal returns for each sector, and only describes and interprets the general statistics and curves of investor sentiment.

To calculate the sectoral indices, the daily and company-specific sentiment indicators must be weighted based on the market capitalization within the sector. Thus, in an additional step, the daily market capitalization was first calculated as a multiplication of outstanding shares and stock price and then set in relation to the total (= sum) market capitalization of all companies belonging to the respective sector and included in the sample, ensuring that larger companies also have a correspondingly higher share of “sector sentiment” and that the calculated sector sentiment thus develops based on the actual company weighting within the sectors. This additional calculation step results in a sector-based sentiment value, available daily, for all eleven sectors considered according to the GICS.

Both the sentiment indicators of the individual companies and OSI can take any value, with higher values indicating a higher (sectoral) sentiment and vice versa. However, a high (sectoral) sentiment does not automatically mean that all the companies included also show a high sentiment. Instead, the (sectoral) indicator indicates a weighted average view of the companies included.

5.2 Design and Data Collection of the Event Study

This subchapter describes the second stage of the study, i.e., the research design and data collection methodology for the event study, which is applied to examine the impact of selected COVID-19 events on stock prices and stock price volatility. The rules for sample formation are explained, followed by a detailed description of the construction and calculation method of the event study for this investigation and outlining the various sub-steps leading to the final result.

The following section is based on MacKinlay's (1997) ideal/typical structure for conducting an event study. Each section describes one step of the procedure proposed in the 1997 study.

5.2.1. Event(s) of Interest and Length of the Event Window

It is crucial to decide on the relevant event(s) to be investigated to determine significant changes within the (sector-specific and company-specific) sentiment indicators and compare the course of the sectoral sentiment indices.

The events investigated in this dissertation were determined using a two-stage procedure. In the first step, previously published event studies on the impact of COVID-19 on the stock markets in general and individual sectors were reviewed for the event dates used in each case. This analysis shows two patterns: Firstly, many studies refer to the first confirmed positive COVID-19 case in the country or market whose index is to be examined (Alam *et al.*, 2021; He *et al.*, 2021; Sayed & Eledum, 2023). Secondly, several event studies choose March 11th, 2020, i.e., the declaration of a global pandemic by the World Health Organization, as a central and globally uniform date for conducting their analysis (Khatatbeh *et al.*, 2020; Maneenop & Kotcharin, 2020).

In the present study, an additional analysis step is to be carried out to more precisely determine the dates relevant to the US market in a second step. Analogous to the procedure by Mavragani & Gkillas (2020) and Brodeur *et al.* (2021), Google Trends is used with a filter for the frequency of US search queries. Google Trends is a freely available tool from Google that checks the frequency of search queries for any search term, over any period, and limited to any existing country. The tool can determine the presence of a topic in the population and the interest in further information, indicating a keyword's relevance in a specific period. Google Trends has been used to investigate the interest in health-related topics (Mavragani & Ochoa, 2019).

The evaluation via Google Trend confirms January 21st, 2020, when the first positive COVID-19 case was confirmed in the US, as a relevant date for the investigation (Figure 8). On this day, the search volume for the term “Corona” (which was the most common term for the new respiratory disease, later specified as COVID-19, at that time, also covering various other search terms such as “coronavirus”, or “corona disease”) rises above the minimum value for the first time. March 11th, 2020, can also be confirmed as a relevant date, with interest in the search term “corona” already at a high level. The third date that can be identified is January 31st, 2020. On this date, Alex Azar, Secretary of Health and Human Services at the time, declared the outbreak of COVID-19 a National Health Emergency (American Hospital Association, 2020). Google Trends shows a peak in interest in the search term on this day, before interest subsequently declines again. This indicates that the event is significant for the US population and, therefore, also for investors. Therefore, this date will also be considered in the event study.

To summarize, and as described in Chapter 3, the following dates will be analyzed in more detail as “events” in this dissertation.:

Event 1; 21.01.2020: First confirmed positive COVID-19 case in the US.

Event 2; 31.01.2020: The declaration of the COVID-19 outbreak as a public health emergency in the US.

Event 3; 11.03.2020: Official declaration of the outbreak of the COVID-19 virus, previously referred to as the COVID-19 crisis, as a global pandemic by the World Health Organization.

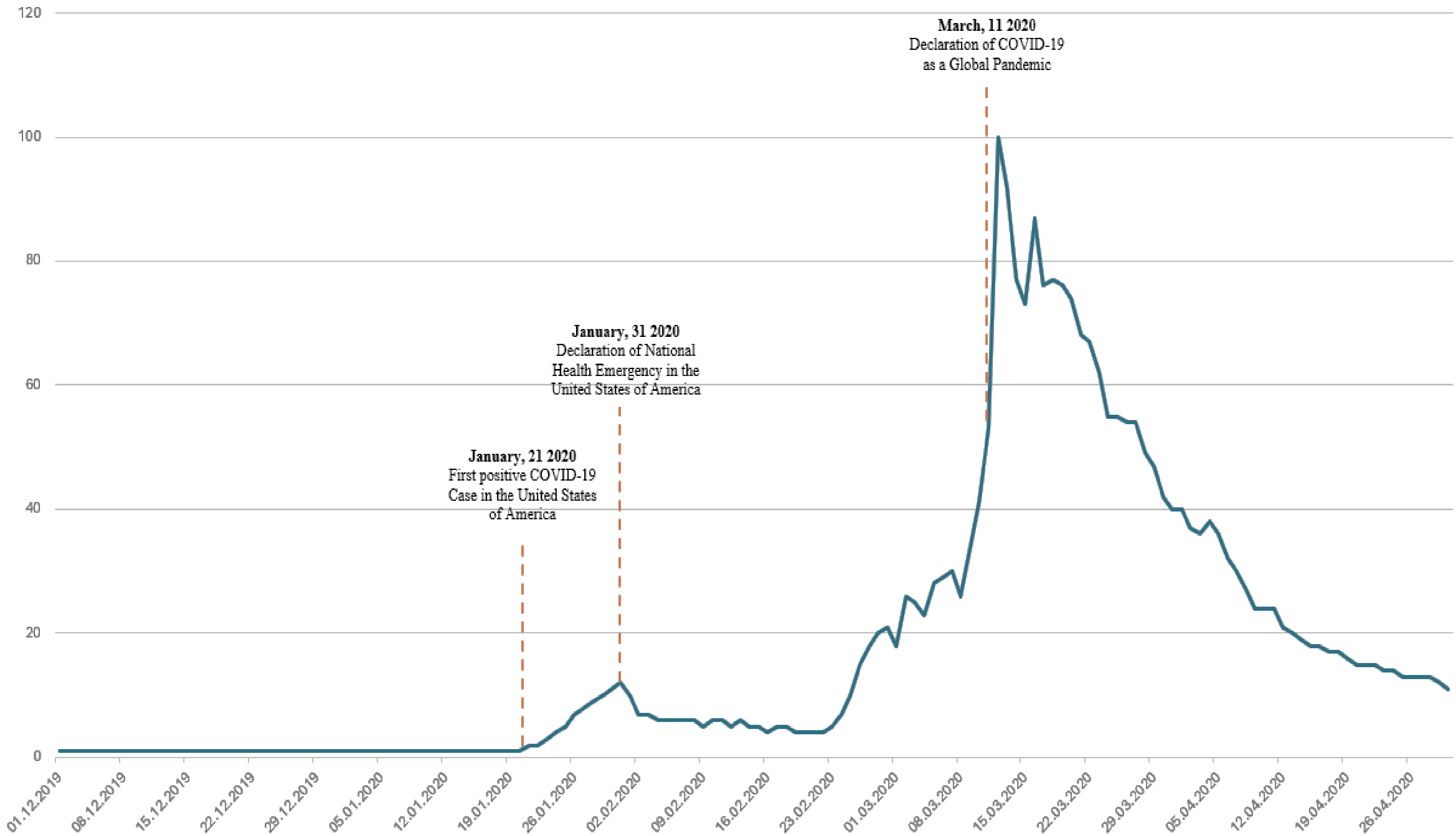

Figure 8. Google Trends for "Corona" in the United States of America, December 2019 - April 2020

Source: own compilation based on data obtained from Google Trends, https://trends.google.de/trends/ (as of August, 27th, 2024).

Following the crucial remarks by McWilliams and Siegel (1997), it needs to be checked whether events have a financial impact, can be seen as largely unanticipated by the market participants, and provide news to the market. In this study, it is assumed that market participants were aware of the potential financial impact of these events. Firstly, it can be assumed that every significant announcement about the development of the COVID-19 pandemic can be seen as an event with a potential financial impact. Secondly, as early as January 4th, 2020, WHO reported the occurrence of a pneumonia cluster in Wuhan, and on January 13th, the first case outside China was confirmed (Mavragani & Gkillas, 2020). Thus, market participants were aware of the virus, which was still referred to as the "novel coronavirus" at the time, and the economic impact of the Chinese government's initial containment measures was already visible.

Even though market participants had to assume that the virus might also reach the US, it had only occurred in Asian countries until the first confirmed case in the United States. The declaration of a public health emergency and the declaration of a pandemic by the WHO were also events that market participants could not have expected and represented new information at the time.

In order to determine the correct event window for these three events, several aspects need to be considered. First, according to MacKinlay (1997) and McWilliams & Siegel (1997), the event window should include the event date and be kept as short as possible. However, according to MacKinlay, the event period can be extended if periods surrounding the event should also be examined, mainly because the market may learn about the information before the event, leading to abnormal pre-event returns (MacKinlay, 1997).

In many similarly designed event studies that deal with the check for abnormal returns following exogenous shock situations, the observation period starts immediately after the time of the event. This is based on the assumption that the event with the effect of an (exogenous) shock situation occurs completely unexpectedly and, therefore, could not be anticipated beforehand. This is also a necessary prerequisite for determining cumulative abnormal returns, as the anticipation of an event reduces the uncertainty of market participants and thus either prevents the emergence of CARs or ensures excess or short returns at an earlier point in time (Guo & Mech, 2000; Cheng *et al.*, 2007). This basic assumption may not be applicable in the case of the COVID-19 pandemic. As already explained, the appearance and international spread of the SARS-COV-2 virus had already been present in the media since the end of 2019. The fact that the US would also be affected by a first case could, therefore, have been anticipated earlier. Once the first case has occurred, it can be assumed that investors could also anticipate further measures, such as the "lockdowns" imposed in the People's Republic of China in mid-January.

In order to take this possibility of earlier anticipation of events into account as far as possible in the present study, three observation logics and three event window lengths are defined in the sense of an explorative approach and in line with the proposal by Krivin *et al.* (2003). This is done to examine event windows *ad hoc* and flexibly based on the sample of the "recognizable" course of the returns, which were summarized in a total of three "panels" (Table 5).

Table 5. Overview of the Different Test Scenarios

Panel 1	Scenario No.	Event Date	Length of Observation Period [Trading Days]	Event Window
	a1	21.01.2020	3	17.01 - 22.01
	b1	21.01.2020	5	16.01 - 23.01
	c1	21.01.2020	7	15.01 - 24.01
	d1	31.01.2020	3	30.01 - 03.02
	e1	31.01.2020	5	29.01 - 04.02
	f1	31.01.2020	7	28.01 - 05.02
	g1	11.03.2020	3	10.03 - 12.03
	h1	11.03.2020	5	09.03 - 13.03
	i1	11.03.2020	7	06.03 - 16.03
Panel 2	**Scenario No.**	**Event Date**	**Length of Observation Period[Trading Days]**	**Event Window**
	a2	21.01.2020	3	21.01 - 23.01
	b2	21.01.2020	5	21.01 - 27.01
	c2	21.01.2020	7	21.01 - 29.01
	d2	31.01.2020	3	31.01 - 04.02
	e2	31.01.2020	5	31.01 - 06.02
	f2	31.01.2020	7	31.01 - 10.02
	g2	11.03.2020	3	11.03 - 13.03
	h2	11.03.2020	5	11.03 - 17.03
	i2	11.03.2020	7	11.03 - 19.03
Panel 3	**Scenario No.**	**Event Date**	**Length of Observation Period [Trading Days]**	**Event Window**
	a3	21.01.2020	3	16.01 - 21.01
	b3	21.01.2020	5	14.01 - 21.01
	c3	21.01.2020	7	10.01 - 21.01
	d3	31.01.2020	3	29.01 - 31.01
	e3	31.01.2020	5	27.01 - 31.01
	f3	31.01.2020	7	23.01 - 31.01
	g3	11.03.2020	3	09.03 - 11.03
	h3	11.03.2020	5	05.03 - 11.03
	i3	11.03.2020	7	03.03 - 11.03

Source: own compilation.

Panel 1 includes event windows symmetrical around each event day (effective day). Each window in this panel begins before the event date and ends after the event date. The following event windows are analyzed: (-1,+1), (-2,+2), (-3,+3). Event windows in Panel 2 begin with the event date (the date of the event is included), covering such windows as (0,+2), (0,+4), and (0,+6). The event period of Panel 3 begins before the event and ends with the event date itself. The respective event date is always included in the event window, resulting in the following event windows: (-6,0), (-4,0), (-2,0). The event window lengths are set at three, five, and seven trading days, respectively, corresponding to frequently selected observation periods in comparable event studies (Das & King 2021), covering very short and rather long event windows. This results in 27 different observation scenarios distributed across the three panels.

5.2.2 Determination of the Selection Criteria for the Sample

The following section describes the methodology used to form the sample for this study, focusing on the procedure for excluding companies from the sample to ensure a valid and reliable measurement of the study's subject without the impact of confounding events. As described in Chapter 4, selecting the sample, i.e., the companies to be included, is crucial for the quality of the research design and, thus, the final result.

Building the Research Sample based on the S&P 500 Index

As an ex-ante assumption, the S&P 500 index in the composition at the time of the events has been defined as the basis for this investigation's sample. For this reason, the 500 companies included in this index at the time of the respective events represent the study population. The companies in the S&P 500 index are distinguished by the fact that they are the largest companies in terms of market capitalization and are headquartered in the US. To achieve the final sample, this population must be revised in the next step using the procedure for confounding events described in Chapter 4.

To increase the quality of the sample, it is necessary to identify and exclude companies from the determined population that could potentially distort the measurement results based on the "COVID-19 crisis" events. According to Brown and Warner and as described in Chapter 4, this is particularly essential when conducting an event study, as non-compliance with the (rather strict) basic assumptions can lead to less precise results (Brown & Warner, 1980; Brown &

Warner, 1985). Companies can only be included in the study if they are not subject to any other internal or external events (confounding events) within the event window, which could influence the event's effect (McWilliams & Siegel, 1997; Blajer-Gołębiewska & Nowak, 2024). To further increase the quality of the study, companies were also excluded from the target group if significant events occurred before the event under investigation. This was done because, especially in the wake of the COVID-19 pandemic, significant spill-over effects could emerge from earlier events during the development and spread of the virus. In the present study, companies excluded from the sample due to confounding events were neither included in the calculation of (sector-related) investor sentiment nor in the event study. This was done because it is also essential for calculating and analyzing (sector-related) sentiment development to exclude possible confounding factors during the period surrounding the events to obtain as realistic a view as possible of sentiment development in the various sectors.

As the course of the COVID-19 crisis is challenging to narrow down in terms of time and spill-over effects may occur due to events immediately before or after the event dates (events that become known immediately after the events could also be anticipated by investors at an earlier point in time), a broad exclusion of potentially affected companies is carried out in this study. Thus, all companies that experienced significant events between November 1st, 2019 (when the first cases of the respiratory disease not yet specifically named at that time became known) and April 30th, 2020, were excluded from the sample. To do so, a two-step procedure (as described below) was used to identify possible interfering events.

In the first step, the notifications under the so-called Securities Exchange Act of 1934 to inform shareholders or the US Securities and Exchange Commission (SEC) about specific events, as proposed by Foster (1980), were first analyzed. Under this law, companies in the US with more than 10 million USD in listed assets and more than 500 shareholders (this regularly applies to all companies included in the S&P 500 index) are obliged to publish an 8-K notification within four working days of the occurrence of certain events within the company (SEC, 2023). Notifications consider such events as modifications to shareholder rights, senior officer appointments and departures, disclosures of financial statements, and others as listed in Table 6. This information obligation increases transparency and is intended to prevent distortion of competition by minimizing an information imbalance between principal and agent. All events listed by the companies under the Securities Exchange Act were examined in detail as part of the sampling process. The companies in question were excluded from the sample.

Table 6. Events Leading to a Filing of an 8-K

An Event That Leads to the Mandatory Filing of an 8-K
• signing, amending, or terminating material definitive agreements not made in the ordinary course of business, bankruptcies, or receiverships • mine shutdowns or violations of mine health and safety laws • consummation of a material asset acquisition or sale • results of operations and financial condition, creating certain financial obligations, such as the incurrence of material debt • triggering events that accelerate material obligations (such as defaults on a loan) • costs associated with exit or disposal plans (layoffs, shutting down a plant, or material change in services or outlets) • material impairments • delisting from a securities exchange or failing to satisfy listing requirements • unregistered equity sales (private placements) • modifications to shareholder rights • change in accountants • determinations that previously issued financial statements cannot be relied upon • change in control • senior officer appointments and departures • directors' elections and departures • amendments to certificate/articles of incorporation or bylaws • changes in the fiscal year • trading suspension under employee benefit plans • amendments or waivers of the code of ethics • changes in shell company status • results of shareholder votes • disclosures applicable to issuers of asset-backed securities • disclosures necessary to comply with Regulation FD • other material events • certain financial statements and other exhibits.

Source: own compilation based on SEC, 2023.

In the second step, additional news were taken into consideration, published in online media in connection with the companies under consideration. The source used for this investigation step was Google News. Not every event in the event window immediately led to an exclusion from the sample—the exclusion was made based on a qualitative assessment by the author of this study, based on the confounding events described by McWilliams and Siegel (McWilliams & Siegel, 1997) and other authors (e.g., Blajer-Gołębiewska & Nowak, 2024). They describe events such as the declaration of dividends, the announcement of a merger, the signature of a significant contract, or the announcement of a new product.

Table 7. Companies Excluded from the Sample

Ticker	Company Name	Ticker	Company Name	Ticker	Company Name
AOS	A. O. Smith	HOLX	Hologic	SNPS	Synopsys
ABBV	AbbVie	HST	Host Hotels & Resorts	SYY	Sysco
ACN	Accenture	HWM	Howmet Aerospace	TMUS	T-Mobile US
AAP	Advance Auto Parts	IBM	IBM	TROW	T. Rowe Price
AFL	Aflac	INTC	Intel	TPR	Tapestry, Inc.
ALB	Albemarle Corporation	IPG	Interpublic Group of Companies (The)	TSCO	Tractor Supply
MO	Altria	INTU	Intuit	TWTR	Twitter
AMCR	Amcor	IQV	IQVIA	UDR	UDR, Inc.
AEE	Ameren	IRM	Iron Mountain	UAL	United Airlines Holdings
AMT	American Tower	JNPR	Juniper Networks	UNH	UnitedHealth Group
AWK	American Water Works	KEY	KeyCorp	UHS	Universal Health Services
AON	Aon	KEYS	Keysight	VTRS	Viatris
AIV	Apartment Investment & Management	KMB	Kimberly-Clark	V	Visa Inc.
APTV	Aptiv	KSS	Kohl's	WBA	Walgreens Boots Alliance
AJG	Arthur J. Gallagher & Co.	KHC	Kraft Heinz	WEC	WEC Energy Group
T	AT&T	LDOS	Leidos	WFC	Wells Fargo
ATO	Atmos Energy	LMT	Lockheed Martin	WDC	Western Digital
AZO	Autozone	MPC	Marathon Petroleum	WHR	Whirlpool Corporation
BAX	Baxter International	MKTX	MarketAxess	WTW	Willis Towers Watson
BDX	Becton Dickinson	MAS	Masco	XEL	Xcel Energy
BBY	Best Buy	MA	Mastercard		
BLK	BlackRock	MRK	Merck & Co.		
BA	Boeing	META	Meta Platforms		
BWA	BorgWarner	MET	MetLife		
BSX	Boston Scientific	MGM	MGM Resorts		
AVGO	Broadcom Inc.	MU	Micron Technology		
CHRW	C.H. Robinson	MHK	Mohawk Industries		
CAH	Cardinal Health	MCO	Moody's Corporation		

CNP	CenterPoint Energy	MS	Morgan Stanley
SCHW	Charles Schwab Corporation	NWL	Newell Brands
CMG	Chipotle Mexican Grill	NI	NiSource
CMS	CMS Energy	JWN	Nordstrom
CTSH	Cognizant	OXY	Occidental Petroleum
DHR	Danaher Corporation	ODFL	Old Dominion
DVA	DaVita Inc.	OMC	Omnicom Group
DLR	Digital Realty	ORCL	Oracle Corporation
DER	Duke Realty	PYPL	PayPal
DD	DuPont	PBCT	Peoples United Financial
EBAY	eBay	PEP	PepsiCo
LLY	Eli Lilly and Company	PSX	Phillips 66
EQIX	Equinix	PPL	PPL Corporation
EL	Estée Lauder Companies (The)	PLD	Prologis
ES	Eversource	PVH	PVH Corp.
EXC	Exelon	QRVO	Qorvo
EXPE	Expedia Group	RF	Regions Financial Corporation
FFIV	F5, Inc.	ROK	Rockwell Automation
FRT	Federal Realty	RCL	Royal Caribbean Group
FLIR	FLIR Systems	SPGI	S&P Global
FLS	FlowServe	CRM	Salesforce
FOXA	Fox Corporation (Class A)	SLB	Schlumberger
GL	Globe Life	NOW	ServiceNow
HBI	Hanesbrands	SPG	Simon Property Group
HRB	H&R Block	SJM	J.M. Smucker Company (The)
HIG	Hartford (The)	SWK	Stanley Black & Decker
PEAK	Healthpeak	STT	State Street Corporation

Source: own compilation.

Many aspects have already been covered by the 8-K filings mentioned before. Nevertheless, an additional step was carried out to increase data quality. Companies were excluded from the sample if the event had the potential to distort the "normal returns" irrationally in terms of size and relevance for the respective company.

After carrying out both steps, 133 companies, as presented in Table 7, were removed from the sample. The specific reasons for exclusion can be found in more detail in Appendix B.

In the third step, once the data for the remaining companies had been determined, some individual value pairs (date and corresponding value) had to be removed from further calculation. This was particularly the case where a company's daily return was 0. In this case, the Adjusted Turnover Rate (ATR) calculation is impossible due to the underlying formula. In line with Foster (1980), these individual daily values were removed from the entire sample. The remaining sample consists of 367 companies, all of which are included in the S&P 500 index and can be broken down by sector according to GICS (Table 8).

Table 8. Distribution of Companies in the Final Sample by Sectors

GICS Sector	Total Number of Companies in S&P 500	Number of Remaining Companies for Further Research
Communication Services	22	19
Consumer Discretionary	56	38
Consumer Staples	33	29
Energy	23	19
Financials	67	49
Health Care	64	41
Industrials	70	62
Information Technology	76	48
Materials	29	26
Real Estate	30	19
Utilities	30	17
Total	500	367

Source: own compilation.

5.2.3 Definition of the Estimation Window, Calculation of Normal and Abnormal Returns

Definition of the Estimation (Observation) Window

Analogous to McWilliams & Siegel (1997), the estimation (observation) window forms the basis for calculating normal returns. It should be noted that the selected window should be long enough to reflect average "normal" returns, yet short enough to avoid being affected by macroeconomic changes in the framework conditions, which could, in turn, impact the formation of normal returns. According to Krivin *et al.* (2003), the observation window can range from a few days and several years.

In this study, the observation window was selected based on the data used to calculate the sentiment indicator: An observation window that only covers periods in which the COVID-19 virus was already known could already be influenced and, therefore, not provide correct normal returns. It is, therefore, necessary to set the observation window to the time before the COVID-19 virus became known. This study defined the period between January 2nd, 2019, and the respective event time as the basis for calculating the normal returns.

The length of the observation windows is therefore:

02.01.2019 – 20.01.2020: 264 trading days

02.01.2019 – 30.01.2020: 272 trading days

02.01.2019 – 10.03.2020: 299 trading days

Calculation and Aggregation of Abnormal Returns

The expected returns for the selected securities during the period under review must first be determined as a basis for calculating the abnormal returns.

In this study, the daily returns are calculated using the formula

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + e_{i,t}$$

where α represents the intercept and β represents the "market beta", both need to be estimated.

The difference between the expected return and the actual daily return is now used to calculate the so-called abnormal return, which quantifies the reaction to the respective event. To aggregate the abnormal returns to cumulative abnormal returns, the abnormal returns determined along the defined study scenarios are summed, which enables an overall view of the event's cumulative effects. The combination of the three approaches with the varying lengths of the observation periods results in a total of 27 investigation scenarios (3 x 9 individual elements in the panels), analogous to the described panels in Table 5.

Statistical Analysis and Robustness of the Sample

Chapter 4 explains that various statistical test procedures are suitable for checking the significance of the (cumulative) abnormal returns. Before deciding on a specific test procedure, the sample must be checked for the applicability of the desired procedure. It is imperative to ensure that the basic assumptions are not violated, as this would drastically reduce the credibility of the event study (McWilliams & Siegel, 1997). Typically, in the case of a time series, such as the data basis applied in this study, the normal distribution of the data in the sample is the basic assumption for applying parametric test procedures. This can be derived from the "efficient market hypothesis", in which risk and return are linked in a linear relationship (Fama, 1970). Only if a sample is distributed equally or normally, this assumption holds true. In practice, however, it has often been proven that markets exhibit inefficiencies and that normality cannot be assumed without further testing (Khang & Huq, 2012). Although Chion & Veliz, among others, determine that samples collected over a longer time horizon generally approximate the normal distribution (Chion & Veliz, 2008), the present sample should also be examined in more detail first.

Normality can be tested visually and using various test procedures (Das & Imon 2016). For this reason, normality is first checked for each of the described observation scenarios a1 – i3 (as described in Table 5) using four independent tests:

- Doornik Hansen test
- Shapiro Wilk W test
- Lilliefors test
- Jarque-Bera test

The above-mentioned tests' results for panels 1-3, with 9 series in each, are presented in Table 9.

Table 9. Results of the Tests for Normality of the Abnormal Returns

Panel 1	a1	b1	c1	d1	e1	f1	g1	h1	i1
Doornik-Hansen test	61.182	26.900	35.360	1018.290	1679.530	545.803	53.428	176.181	75.625
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shapiro-Wilk W	0.938	0.962	0.975	0.654	0.7362	0.798	0.957	0.136	0.925
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lilliefors test	0.100	0.071	0.056	0.144	0.119	0.123	0.064	0.136	0.092
p-value	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera test	159.906	67.253	48.042	47067.500	1982.200	9631.870	227.476	1087.680	362.314
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel 2	**a2**	**b2**	**c2**	**d2**	**e2**	**f2**	**g2**	**h2**	**i2**
Doornik-Hansen test	35.632	36.041	52.156	1003.200	243.553	425.999	31.425	59.781	20.757
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shapiro-Wilk W	0.965	0.964	0.964	0.621	0.736	0.865	0.964	0.938	0.977
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lilliefors test	0.070	0.074	0.076	0.170	0.152	0.102	0.082	0.074	0.056
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera test	58.502	56.213	76.244	57016.900	27109.400	2582.760	88.195	223.421	43.784
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel 3	**a3**	**b3**	**c3**	**d3**	**e3**	**f3**	**g3**	**h3**	**i3**
Doornik-Hansen test	66.850	184.988	157.914	86.756	64.397	64.213	526.818	339.589	307.098
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shapiro-Wilk W	0.943	0.937	0.939	0.941	0.956	0.950	0.754	0.799	0.810
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lilliefors test	0.083	0.067	0.064	0.074	0.074	0.054	0.147	0.136	0.134
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera test	182.972	449.494	827.775	459.822	195.661	308.823	5023.520	2707.640	2141.940
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: own compilation.

The results of all tests showed that the sample is not normally distributed at the significance level of $p = 0.01$. Consequently, there is a violation of acceptance for parametric test procedures. Therefore, these test procedures cannot be used.

5.2.4 Test Procedure Used for the Current Investigation

Taking the above considerations into account, in this study, the Generalized Sign Test (or Generalized Sign Z) will be used. The nonparametric test procedure, first described by Cowan, Nayar, and Singh (1990) and Sanger and Peterson (1990), provides reliable results, even in the presence of non-normality, increasing variance, or an increase in the event period (Cowan, 1992). The method is based on the proportion of positive CARs over the observation period.

5.3 Conduction of the Volatility Analysis

To analyze the volatility, the abnormal return on the specific event day (γ) is first determined using a GARCH model, as described in Chapter 4. The value obtained for γ is then used using the formulas described in Chapter 4 and tested for significance using the test procedure introduced by Savickas (2003) as described in Chapter 4. In this study, the named parameters are estimated based on the returns from the existing sample of 334 data records from the same number of trading days (from 02.01.2019 to 30.04.2020).

Both the widely used cross-sectional test statistics, as mentioned by Brown and Warner (1980), and Savickas' (2003) model, applied by Balaban and Constantinou (2006), are used without any further adaptations, as their applicability for the present sample is given. The test is based solely on whether the volatility determined on the event day differs significantly from the “normal” volatility.

5.4 Determination of the Role of Company-specific Investor Sentiment in Moderating the Impact of Exogenous Shocks on Stock Prices

The following section deals, in particular, with the procedure for dividing the sample into “high” and “low” sentiments and the test setup for hypothesis testing. To test the Moderating Effect Hypotheses H4a, H4b, and H4c and determine the role of company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices, the sample is first divided into distinct groups based on company-specific sentiment. Specifically, the “investor sentiment" surveyed as a metric variable is converted into an ordinally scaled variable with three characteristics ("high", "medium", and "low"). The classification looks at investor sentiment values on the day of the event under review, i.e., immediately before any possible changes due to the event itself. There are different approaches to this in the literature. Bouteska *et al.* define "high" investor sentiment as the sentiment that is at least one standard deviation above the mean value of the sentiment benchmark/sample (Bouteska *et al.*, 2019), while "low" sentiment deviates negatively from the mean value by at least one standard deviation. All other values also fall into the "medium" category. In addition, a classification can be done based on the mean or median of the sample. Further differentiation arises when calculating the mean value, as this can be carried out cross-sectionally and on an individual company basis or in relation to the entire sample of all companies. Table 10 shows a breakdown of the 367 companies in the sample based on the various criteria at each of the three event dates examined.

Table 10. Distribution of Companies by Investor Sentiment Across Different Classifications

Classification method	Sentiment			Total
	High	Low	Medium	
		21.01.2020		
mean (cross-sectional)	191	176	-	367
mean (individual company)	220	147	-	367
median (cross-sectional)	182	185	-	367
std. dev. of ind. company sentiment	99	42	226	367
		31.01.2020		
mean (cross-sectional)	171	196	-	367
mean (individual company)	120	247	-	367
median (cross-sectional)	184	183	-	367
std. dev. of ind. company sentiment	43	134	190	367
		11.03.2020		
mean (cross-sectional)	176	191	-	367
mean (individual company)	10	357	-	367
median (cross-sectional)	186	181	-	367
std. dev. of ind. company sentiment	0	324	43	367

Source: own compilation.

In the case of the classification methods based on the "mean" and "median", a distinction is only made between the two categories: higher / lower than the mean (median). In the case of the criterion “standard deviation”, the additional category “medium” is present, if the IS of the analyzed company lies within the range between a positive and a negative standard deviation.

Table 10 shows that the approach chosen by Bouteska *et al.* (2019) does not seem useful for the present study due to the high number of companies with “medium” sentiment and, in particular, at the time of the event on March 11th, 2020, due to the unequal group sizes in the sample. This approach is, therefore, not considered further for the subsequent calculation steps.

The remaining three approaches, combined with the varying lengths of the observation periods, resulted in 81 investigation scenarios (3x 27 individual elements in the panels; Table 11).

Table 11. Overview of the Various Test Scenarios for the Moderating Effect Hypotheses

Event Date	Scenario No.	Length of Observation Period [days]	Observation Period	Classification Method
		Panel 1		
21.01.2020	a1	3	17.01.-22.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	b1	5	16.01. - 23.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	c1	7	15.01. - 24.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	d1	3	30.01. - 03.02.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	e1	5	29.01. - 04.02	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	f1	7	28.01. - 05.02	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	g1	3	10.03. - 12.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	h1	5	09.03. - 13.03.	mean (cross-s.) mean (ind. com) median (cross-s.)

11.03.2020	i1	7	06.03. - 16.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
		Panel 2		
21.01.2020	a2	3	21.01.- 23.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	b2	5	21.01.- 27.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	c2	7	21.01.- 29.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	d2	3	31.01. - 04.02.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	e2	5	31.01. - 06.02.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	f2	7	31.01. - 10.02.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	g2	3	11.03. - 13.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	h2	5	11.03. - 17.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	i2	7	11.03. - 19.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
		Panel 3		
21.01.2020	a3	3	16.01. - 21.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	b3	5	14.01. - 21.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
21.01.2020	c3	7	10.01. - 21.01.	mean (cross-s.) mean (ind. com)

				median (cross-s.)
31.01.2020	d3	3	29.01. - 31.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	e3	5	27.01. - 31.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
31.01.2020	f3	7	23.01. - 31.01.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	g3	3	09.03. - 11.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	h3	5	05.03. - 11.03.	mean (cross-s.) mean (ind. com) median (cross-s.)
11.03.2020	i3	7	03.03. - 11.03.	mean (cross-s.) mean (ind. com) median (cross-s.)

Source: own compilation.

The significance test is then carried out using the non-parametric Mann-Whitney U test to analyze the groups' rank sums. At the same time, the median test is carried out to verify the findings based on the groups' medians.

Chapter 5 describes the application of the methods described in detail in Chapter 4 in the research context and in the specific application to the research question and sample of the present study. In particular, it describes in detail how the quality of the study is ensured on the one hand by the thorough approach to compiling the sample and selecting the event times, and on the other hand by the use of suitable test procedures. The procedure described in Chapter 5 ensures that the empirical study results presented in the following chapter provide valid statements to answer the research questions.

CHAPTER 6
EMPIRICAL STUDY RESULTS AND DISCUSSION

This chapter presents the results of the statistical data analysis carried out as part of the dissertation. The analysis is based on empirical tests of theoretical hypotheses as developed in Chapter 3, in order to support the theoretical assumptions with statistical evidence.

First, the most important descriptive statistics for sentiment indicators are analyzed, providing an overview of the characteristics and distribution of the variables applied. Second, the results of Granger's test for causality are described to investigate the relationship between the OSI and the S&P 500 daily returns. Third, statistical testing of the hypothesis on the impact of the exogenous shocks on stock returns and stock volatility is conducted. Finally, the role of investor sentiment in moderating the relationship between the disclosure of new information and stock returns is described in detail. Furthermore, the results are discussed and connected to the context of the COVID-19 outbreak.

Presentation of study results and discussion address Research Questions 4-8, while Research Questions 1-2, focusing on theoretical foundations and existing literature regarding the research problem, were discussed in the theoretical section of the dissertation. Research Question 3, regarding suitable methods of measuring investor sentiment, was discussed in Chapter 4.1. The most suitable approach to measuring IS in the context of this study (Research Question 5) is presented in Chapter 4.2.

6.1 Sentiment Indices

One aspect of Research Question 6 (RQ6) focuses on how exogenous shocks, like the COVID-19 pandemic, impact investor sentiment across companies and sectors (Chapter 1.2). To answer the question, the sentiment course for the companies included in the S&P 500 index and various sectors within the S&P 500 Index was analyzed in more detail using the OSI and sector-based sentiment indicators, both aggregated based on a newly developed aggregation methodology. The following section addresses these aspects before the statistical analysis of the research questions formulated in the hypotheses.

6.1.1 Aggregated Overall Sentiment Indicator

Figure 9 first shows the development of the aggregated OSI calculated for the S&P 500 Index for the period between January 2nd, 2019, and April 30th, 2020. It is worth noting that the OSI was not determined based on the key figures of the actual S&P500 Index but, for the purposes of this study, was aggregated based on calculated individual sentiment trends for the companies included in the index, weighted by their market capitalization.

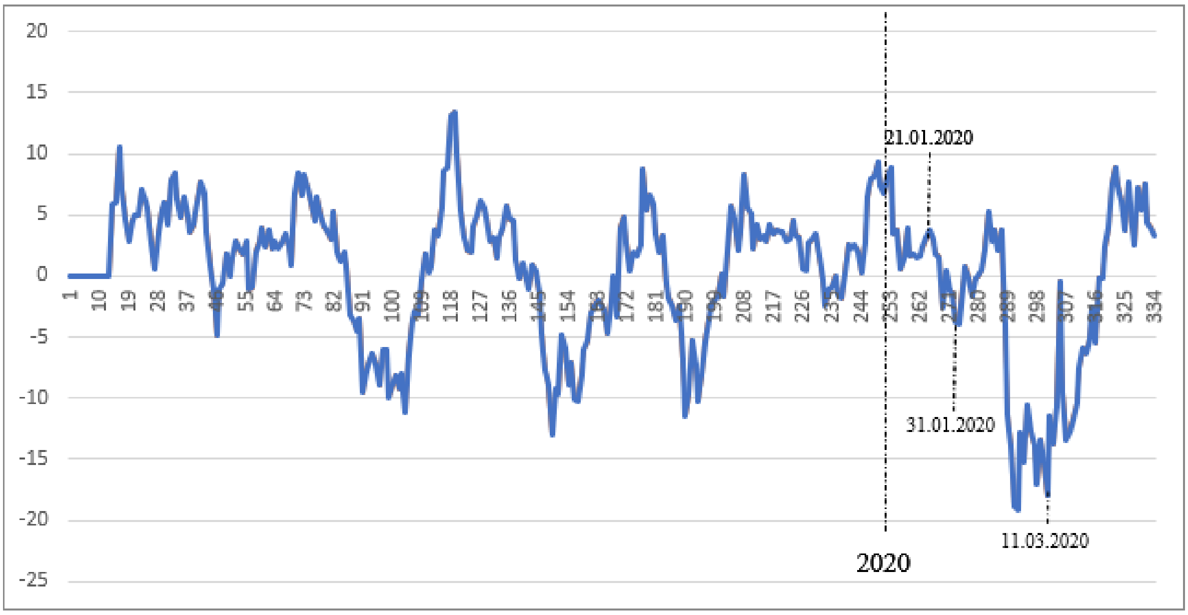

Figure 9. Weighted Sentiment Indicator for S&P 500 Index between 02.01.2019 and 30.04.2020

Source: own compilation.

Visual inspection of the curve shows that the OSI fluctuated significantly between positive and negative values over time, with no apparent visual trend. In 2020, several adverse solid fluctuations can be observed, representing global lows on the curve.

January 21st, 2020 (when the US Department of HHS declared a global health emergency), represents a local high point in investor sentiment. The Investor Sentiment Index rises shortly before this trading day and falls again immediately after the date. January 31st, 2020 (the first confirmed COVID-19 case in the United States), on the other hand, marks a local minimum, with the opposite situation to January 21st, 2020. On January 31st, 2020, the index fell shortly before the event date and rose again. The most dramatic slump in investor sentiment, with the most significant negative amplitude, as shown by the graph's lowest point, occurred after February 24th, when the sentiment index reached its lowest point at almost -20. Despite a thorough review of the news and events surrounding this date, no clear explanation for this dramatic shift could be identified. The second lowest point occurred on March 11th, 2020—the day when the WHO declared the pandemic.

6.1.2 OSI vs Daily News Sentiment Index

Research Questions 3 (RQ3) and 5 (RQ5) focus on how investor sentiment can be measured in general as well as specifically in the context of this dissertation and what methods or indicators best capture its nuances. In Chapter 4.2, the type and calculation of the sentiment indicator that seems best suited to the research questions of this dissertation was determined based on an extensive literature review. To further verify this derivation, the OSI will be compared with another index, the Daily News Sentiment Index, which is based on the systematic analysis of news and, thus, represents a different approach to measuring sentiment.

In 2020, Shapiro, Wilson, and Sudhof presented their Daily News Sentiment Index, determining investor sentiment based on an analysis of economics-related newspaper articles (Shapiro *et al.*, 2020). Specifically, articles from 24 different newspapers are included to determine sentiment for the US market, covering different US regions or having a national focus (Federal Reserve Bank of San Francisco, 2024). Figure 10 shows the comparison between the aggregated, weighted sentiment indicator (OSI) based on the individual companies of the S&P 500 index and the Daily News Sentiment Index in the period between January 2019 and April 2020.

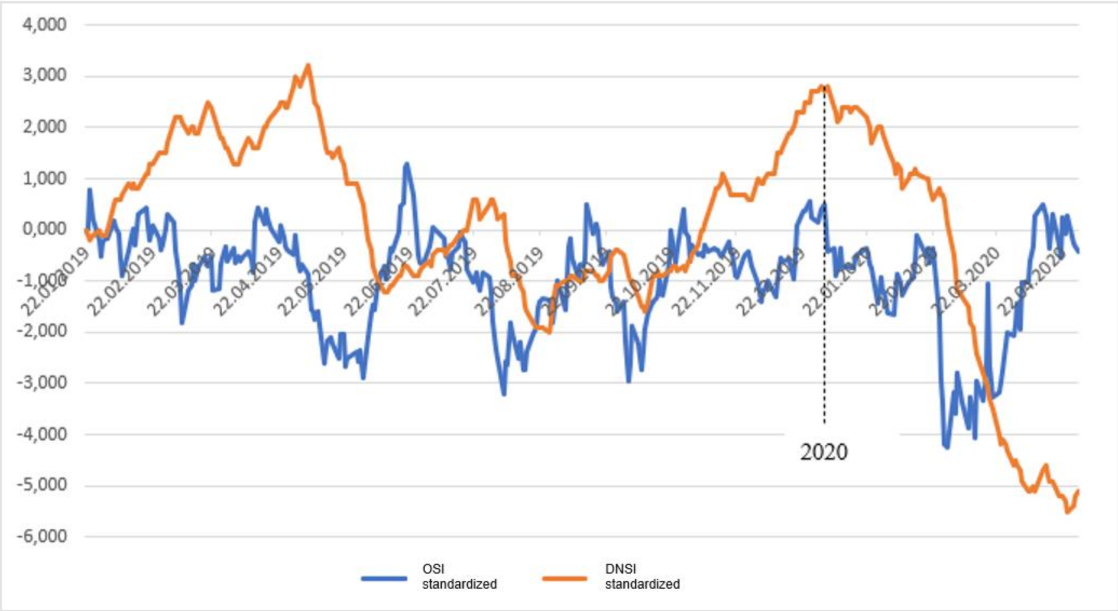

Figure 10. Comparison of Transformed OSI and Transformed Daily News Sentiment Index

Source: own compilation.

Both indices have been transformed based on their value on the first observation day (=0) to make them comparable. This means that every daily value of both indices has been divided by the respective value on the first observation day. 1 is subtracted from these obtained values to start with a common basis of 0 and to make the movements of both indices comparable.

The orange line, which shows the Daily News Sentiment Index course, has a "calmer" and less erratic course compared to the OSI. In 2019, the index fluctuated between -2 in September 2019 and +3.2 in May 2019. At the end of 2019 and the beginning of 2020, the index reached a local peak of around +2.8. After reaching the peak, the index drops until the end of the period under review. Both indices generally show a negative trend, especially in 2020, with the OSI demonstrating more immediate, short-term fluctuations.

The most significant difference between the two indicators is precisely between January and the end of April 2020. While the Daily News Sentiment Index remains negative after falling into negative territory from January 2020, the aggregated sentiment indicator OSI shows an almost equally strong countermovement after a solid negative decline, finally leading investor sentiment back into positive territory. The interpretation of this development will be provided in Chapter 6.2.

6.1.3 Sector-Related Sentiment Indicators

Figures 11, 12, and 13 provide an overview of the weighted sentiment indicators for the eleven sectors according to GICS, comparing each of them to the OSI for the S&P 500 Index, also for the period January 2nd, 2019, and April 30th, 2020.

First, most sectoral indices show similar trends compared to the OSI for the S&P500 index. Only the Utilities and Real Estate sectors show visible differences. In addition, throughout the observed period and particularly between January 2020 and February 2020, the Energy, Consumer Staples, and Healthcare sectors take on values contrary to the sentiment indicator trend for the S&P500 index. Table 12 presents key descriptive statistics for the sector sentiment indices across the entire observation period.

Table 12. Summary Statistics of Sectoral Investor Sentiment Indicators

Variable (Sector)	Mean	Median	Std. dev.	Min	Max
Communication Services	0.18	1.22	5.91	-17.20	13.50
Consumer Discretionary	0.27	1.50	7.85	-19.80	17.70
Consumer Staples	0.13	0.52	5.07	-18.80	14.00
Energy	0.10	1.13	9.51	-20.30	22.00
Financials	0.12	0.46	8.07	-23.80	17.60
Healthcare	0.17	0.61	6.15	-18.60	16.60
Industrials	0.14	0.90	7.60	-19.30	15.50
Information Technology	0.12	1.95	7.61	-21.50	15.60
Materials	0.14	0.81	6.30	-20.50	13.90
Real Estate	0.14	0.11	7.72	-17.60	21.80
Utilities	0.03	0.11	7.41	-20.00	19.30

Source: own compilation.

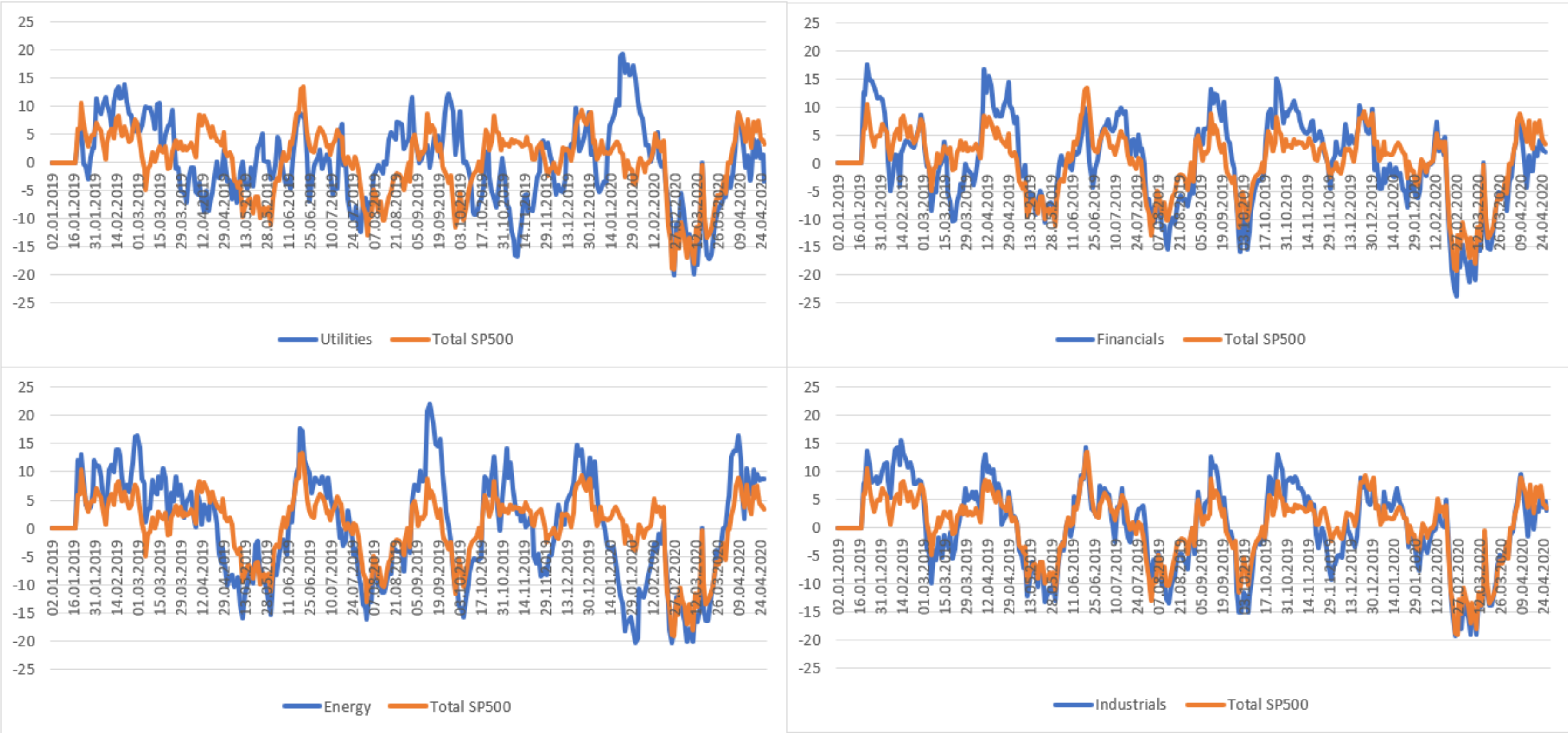

Figure 11. Sectoral Sentiment Indicators (for Utilities, Financials, Energy, and Industrials) in Comparison to the Overall Sentiment Indicator

Source: own compilation.

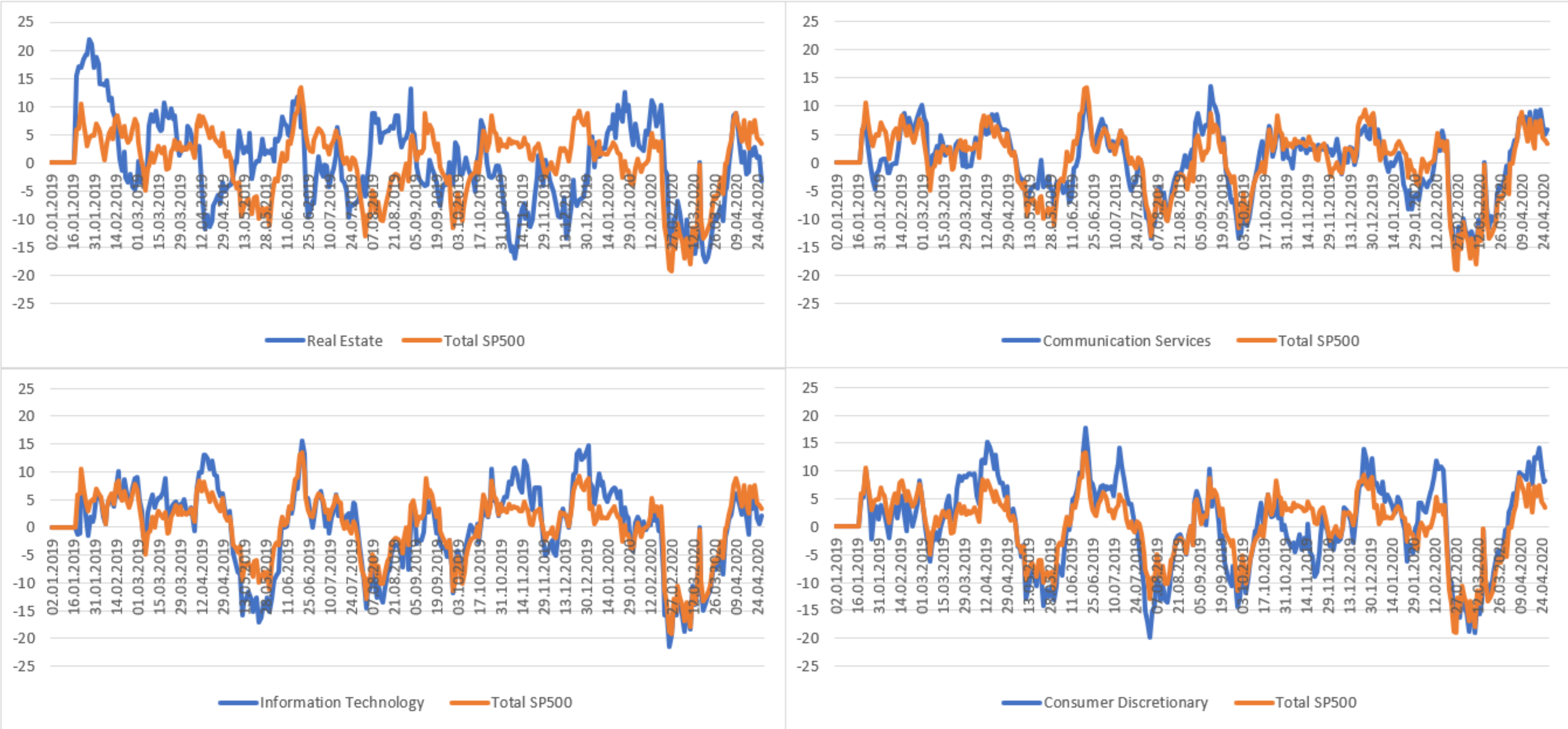

Figure 12. Sectoral Sentiment Indicators (for Real Estate, Communication Services, Information Technology, and Consumer Discretionary) in Comparison to the Overall Sentiment Indicator

Source: own compilation.

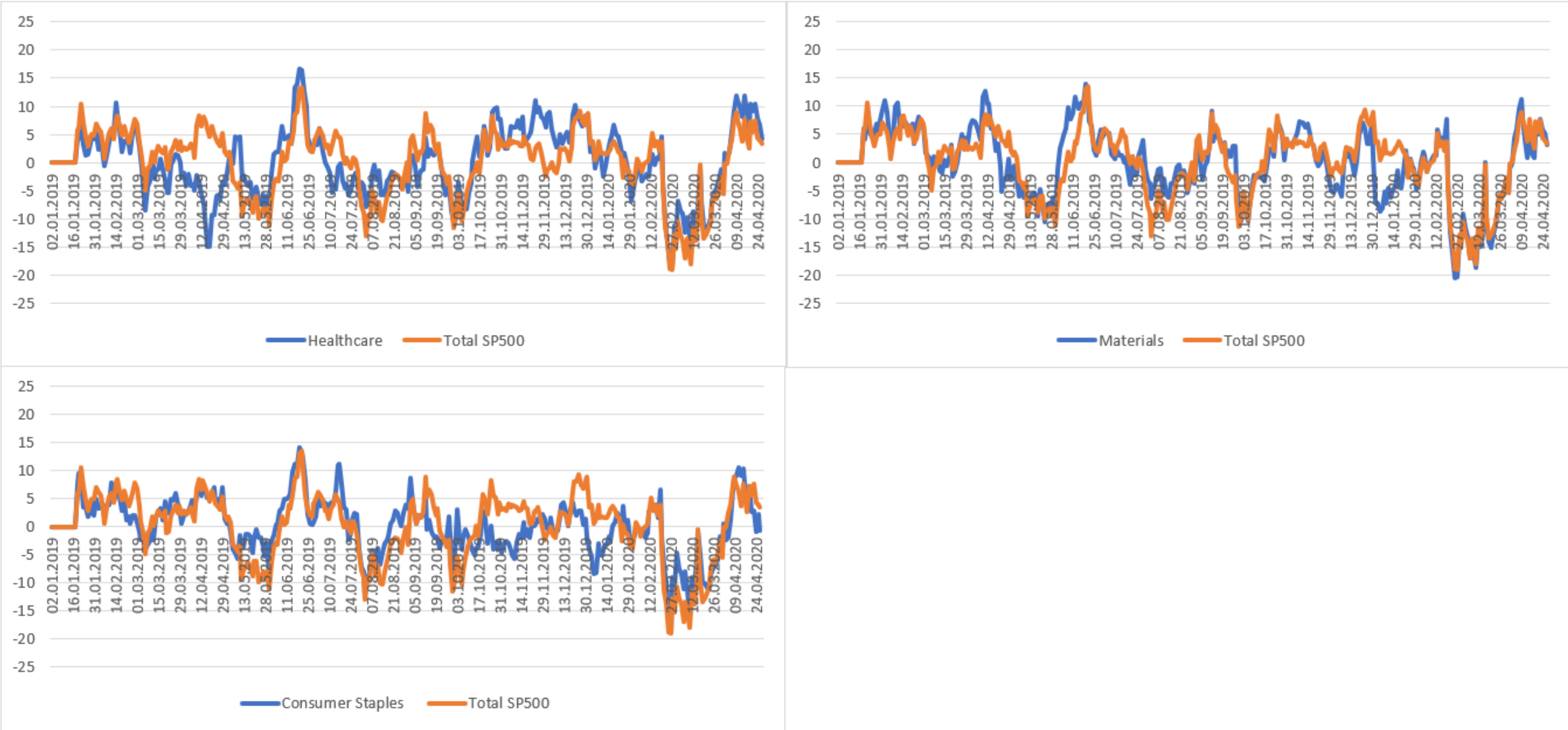

Figure 13. Sectoral Sentiment Indicators (for Healthcare, Materials, and Consumer Staples) in Comparison to the Overall Sentiment Indicator

Source: own compilation

The summary statistics (Table 12) show that the arithmetic means of all sector indices are positive for the observation period, spanning from +0.03 in the Utilities sector to +0.27 in the Consumer Discretionary Sector. The medians, in comparison, exhibit more significant variation across sectors, although all values also remain positive. The Real Estate and Utilities sectors have the lowest median at +0.11, whereas the Information Technology sector has the highest median value (+1.95). Regarding variability, expressed by the sectoral indices' standard deviation, the Energy sector shows the highest value, with a standard deviation of 9.51. In contrast, the Consumer Staples sector shows the least variation, with a standard deviation of 5.07.

The Financials sector has the lowest minimum value of -23.8, while the Energy sector reaches the highest maximum of +22. The range between the minimum and maximum values is smallest in the Communication Services sector, with a difference of 30.7, and most extensive in the Energy sector, at 42.3. In summary, the table reveals considerable differences and variability in sectoral sentiment indices, with the Energy and Financials sectors showing the most extensive ranges in values.

Table 13 provides a comparison of the same key statistical metrics for the same sectors as indicated before, comparing two periods: January–April 2019 in comparison to January–April 2020. The statistics included are again (arithmetic) mean, median, standard deviation, and minimum/maximum values for each sector.

For the means, all sectors, with one exception, experienced positive values in 2019, with the highest value in the Energy sector (+6.55). Healthcare is the only sector with a negative mean (-0.55). However, in 2020, most sectors experienced a significant decline, leading to negative means. Only the Consumer Discretionary sector maintained a barely positive sentiment (+0.03). In contrast, the Energy sector saw the most significant decline, with an arithmetic average in sentiment of -4.84, dropping by more than ten points from +6.55.

An analysis of the median values shows that in 2019, all sectors had positive values, ranging from +0.03 for Healthcare to +6.95 for Industrials. Similar to the arithmetic means, the medians also declined substantially in 2020, with several sectors, such as Energy (-4.66; after +6.41 in 2019) and Industrials (-1.15; after +6.95 in 2019), showing negative median values. However, sectors like Information Technology, Consumer Discretionary, and Real Estate remained positive despite the lower median values.

Table 13. Summary Statistics of Sectoral Sentiment Indicators, Jan–Apr 2019 vs. 2020

Variable (Sector)	Mean Jan-Apr 2020	Median Jan-Apr 2019	Median Jan-Apr 2020	Std. dev. Jan-Apr 2019	Std. dev. Jan-Apr 2020	Min Jan-Apr 2019	Min Jan-Apr 2020	Max Jan-Apr 2019	Max Jan-Apr 2020
Communication Services	-2.24	3.05	-1.70	3.54	7.22	-4.61	-17.17	10.12	9.43
Consumer Discretionary	0.03	3.99	2.85	4.64	9.32	-6.13	-19.05	15.15	14.05
Consumer Staples	-2.49	3.51	1.85	2.81	6.19	-4.08	-18.76	9.54	10.58
Energy	-4.84	6.41	-4.66	4.60	10.56	-6.13	-20.25	16.47	16.43
Financials	-4.98	2.83	-3.23	7.277	7.96	-10.41	-23.79	17.56	9.64
Healthcare	-1.25	0.03	-0.43	5.27	7.37	-14.80	-18.60	10.64	11.87
Industrials	-3.00	6.95	-1.15	5.98	7.86	-9.91	-19.26	15.46	9.57
Information Technology	-2.28	4.78	0.51	3.54	8.58	-2.98	-21.54	13.08	14.66
Materials	-3.73	4.91	-3.11	3.92	7.62	-5.07	-20.49	12.55	11.12
Real Estate	-0.99	5.55	1.39	8.66	8.47	-11.78	-17.57	21.84	12.62
Utilities	-1.22	5.48	-0.37	6.39	9.83	-8.79	-19.98	13.98	19.27

Source: own compilation.

The standard deviation increased in 2020 across most sectors, indicating higher volatility than in the previous year. For instance, the standard deviation in the Energy sector more than doubled from 4.6 in 2019 to 10.56 in 2020. Similarly, the Financials sector experienced a slight increase in standard deviation, while Real Estate marginally decreased in value during the same period.

Considering minimum and maximum values, all sectors experienced a decrease in their minimum values in 2020 compared to 2019. The Financials sector showed the most significant drop from -10.41 in 2019 to -23.79 in 2020. In general, the visual inspection of the graphs shows that every sector experienced a new global minimum value during March 2020. Maximum values remained relatively stable for many sectors between the two periods. However, there were notable declines in sectors such as Industrials, where the maximum value dropped from 15.46 to 9.57, and Real Estate, where the maximum value decreased from 21.84 to 12.62.

In summary, the data shows a clear trend of increased volatility of the sectoral sentiment indicators, expressed through the substantial increases in standard deviations and more negative sentiment in 2020, indicating the influence of external (economic) factors and, most likely, the outbreak and spread of COVID-19. The Energy and Financials Sectors, in particular, exhibited the most extreme shifts in sentiment, with significant drops in average and median and an increased standard deviation.

6.1.4 Understanding Investor Sentiment Behavior during the COVID-19 outbreak

Investor sentiment reflects the optimism or pessimism of financial market participants about a security, a sector, or an index. Based on the results and trends of the aggregated sentiment indicator for the S&P 500 index, it becomes clear that the COVID-19 outbreak impacted market participants' investor sentiment (Table 13, Figures 10, 11, 12, and 13). While sentiment was still largely positive in 2019, the sharp slump surrounding the essential outbreak-related events examined in this dissertation is clearly visible, even based on purely visual inspection (Figure 10). The reasons for this sharp drop in sentiment into negative values may be the significantly increased uncertainty caused by the events of the pandemic, the political interventions introduced, and the resulting economic cuts. The fact that these factors can have a negative impact on investor sentiment has already been explained in earlier chapters of the dissertation.

Looking at the specific event dates, the analysis shows that the sentiment indicator initially falls into hostile areas immediately after the first positive COVID-19 case is reported in the US on January 21st, 2020 (Figure 10). It can be assumed here that the certainty that the “disease caused by the novel coronavirus” has spread beyond the borders of Asia led to this substantial decrease. For S&P 500 index investors, it may then have become more evident that measures such as those already spread by the media from China could also be introduced in the US. This would lead to a much more negative market outlook than before.

January 31st, 2020, marks the local minimum of the sentiment curve, following a clear negative trend since January 21st, 2020. Subsequently, sentiment developed a positive trend. A purely visual inspection does not reveal any (negative) impact of January 31st on investor sentiment. It is, therefore, also not possible to recognize that investors reacted "shocked" in a negative sense to the new information, and consequently, sentiment also adjusted to the negative trend.

This statement initially leaves room for further interpretation and opens up the potential for further research. In research, the term "shock" and the "shocked" reaction in the sense of the efficient market hypothesis always refer to the effect of the investor reaction on stock prices; the effects are visible and measurable in the form of cumulative abnormal returns, for example. However, little research has been done into whether shocks can also be recognized directly in the development of sentiment itself or whether sentiment reacts to unexpected events with a delay or at a slower pace. The emergence of positive or negative "cumulative abnormal sentiment" has not yet been considered in research.

A look at investor sentiment between January 31st and March 11th, 2020, suggests that a "shock" reaction also seems possible in investor sentiment itself. Here, a drop in sentiment value from +5 to almost -20 can be seen within only two trading days (Figure 10). At no other time during the review period did investor sentiment shift with such short-term intensity. There was no other specific event when this strong movement happened. It can be assumed that the sum of the events—the further spread of the COVID-19 disease, and the resulting gradual build-up of uncertainty and insecurity—led to a panic-like change in investor sentiment at this point.

Furthermore, the course of the sentiment graph could already be strongly influenced by the spread of COVID-19 in late February 2020. If this is the case, investors will have already adjusted their expectations to a lower level before the actual (significant) events. Nevertheless, the development of sentiment on the trading day of March 11th, 2020, in particular, can be seen as a reaction to an exogenous shock situation, namely the declaration of the spread of the coronavirus as a global COVID pandemic by the WHO. Therefore, it can be concluded that March 11th is indeed an exogenous shock situation with a strong and visual impact on investor sentiment (Figure 10).

An analysis of the different sectors according to GICS allows comparable conclusions. While the sentiment curves in 2019 are still uneven and show different positive and negative swings, sentiment trends in 2020, especially in the period between February and March 2020, are converging. In all graphs (Figures 11-13), the W-shape of the sentiment curve in the trading days immediately before March 11th, 2020, is clearly visible. The trends in investor sentiment, which develop differently over the observation period depending on the respective sector, differ only slightly following the occurrence of an exogenous shock situation. While investors were previously able to differentiate their sentiment with regard to individual sectors by precisely analyzing market, sector, and company data, this is not possible with the same level of detail and thoroughness immediately after a shock situation. In addition, there may be irrationally driven herd behavior - market participants infect each other in their panic, further reinforcing the negative effect on investor sentiment (Bouri *et al.*, 2021).

Two sectors reveal a particular trend in investor sentiment that requires further interpretation: Utilities and Energy. The Utilities sector showed above-average positive investor sentiment immediately before the sharp decline in February and March 2020 (Figure 11). The Utilities sector includes companies that provide public utilities - these are mainly companies in the electricity, water, and waste disposal sectors. One reason this sector showed outstandingly positive sentiment could be the stricter hygiene requirements resulting from the COVID-19 outbreak and the associated additional expenses in the Utilities sector. In many cases, utilities companies are either operated by the state itself or are partially nationalized, which distinguishes investors' attitudes towards them compared to private companies. Furthermore, a second reason could be that these companies provide essential services that continue to be provided even during economic instability or a slump in demand.

The second sector with a conspicuous sentiment trend in the period around the events considered in the dissertation is the Energy sector. While the Utilities sector showed exceptionally positive sentiment between the end of February and the beginning of March, the Energy sector showed exceptionally negative sentiment (Figure 11). This negative investor sentiment is possibly due to investors' expectations that lockdowns and plant closures could also occur in the US, as was the case in China a few weeks earlier (KPMG, 2020). This would result in a significant reduction in energy consumption by companies, which are much more energy-intensive than private households, which would cloud the outlook for energy-producing companies in the Energy sector.

The development of sentiment during the COVID-19 outbreak is mainly in line with previous findings from other studies. Two studies found a correlation between uncertainty in the context of the pandemic (+) and investor sentiment (-) (Shaikh, 2021, investigating

12 major global markets; Haroon & Rivzi, 2020 for the US market). This is confirmed by the study by Dash and Maitra (2022) on the development of investor sentiment during the COVID-19 pandemic in the G7 countries. This can also be seen in the sentiment trends determined, with the average and median values of the individual sectors from January to April 2020 consistently showing lower levels than a year earlier.

In comparison with the Daily News Sentiment Index (DNSI), according to Shapiro and Wilson, a visual inspection of the curves revealed that the OSI and DNSI do not show parallel trends. In a study by Buckman *et al.* (2020), the authors found that the DNSI has a different course compared to the survey-based measurement of investor sentiment in the context of COVID-19. The DNSI has also not yet been tested for its predictive accuracy concerning the returns of individual securities or stock indices. Shapiro *et al.* (2022), on the other hand, were able to prove that the DNSI can predict the course of survey-based sentiment measures. As the OSI is an index-based indicator, it can be assumed that the functional mechanism of the DSNI is not comparable to that of the OSI (as it is not for other sorts of measurement) and that both indicators, therefore, have their *raison d'être* when used in the correct context.

This study also confirms that different sectors can have different sentiment trends, as shown by other authors (Song, Hao & Lu, 2021). However, this finding is supplemented by the observation that investor sentiment can no longer be differentiated by market participants depending on the sector after an actual panic-like reaction.

Finally, other effects may also have had an indirect impact on investor sentiment in the present study: In their study, Mili *et al.* (2023) found a sensitive reaction of the Psychological Line Index and the Relative Strength Index in the wake of (negative) news on COVID-19. Chebbi *et al.* (2021) also determined that the COVID-19 outbreak reduced average stock liquidity in the S&P 500, which in turn is negatively correlated with trading volume (see the explanations in Chapter 4). All three elements are part of the sentiment indicator constructed for this study, which is why these influences could also have an impact on the shape of the investor sentiment graph.

6.2 Daily OSI as a Predictor of S&P 500 Index Daily Returns

Research Question 4 (RQ4) asks whether investor sentiment measured using a market-based approach a reliable predictor of future security performance (Chapter 1.2). It corresponds to Hypothesis 1 stating that the OSI available on a daily basis, aggregated from the companies included in the S&P 500 index, is capable of predicting the daily returns of the S&P 500 index (Chapter 3.1).

In the following section, the results of the empirical-statistical study on Research Question 4 (RQ4) are discussed in a first step on the basis of the data set collected. In the second part, the results are placed in the context of the COVID-19 outbreak, interpreted, and initial implications are derived.

6.2.1 Market-Based Investor Sentiment vs. the S&P 500 Index

The basis of the sentiment indicator used in this dissertation is an index proposed by Seok *et al.* (2019b), consisting of various sub-indicators. The predictive accuracy of the sentiment indicator, even after the occurrence of news (i.e., earnings news), has already been demonstrated by previous studies based on companies included in the Korean KOSPI index (Seok *et al.*, 2019a; Seok *et al.*, 2019b).

The current dissertation adds a new aspect to the approach of measuring investor sentiment, as initially proposed by Seok *et al.* (2019b). In order to be able to determine the sentiment for the S&P 500 Index with its five hundred individual companies from the eleven sectors according to GICS as precisely as possible, it was aggregated into an overall sentiment indicator (OSI) using the individual, company-specific indicators and based on a weighting of the companies according to their market capitalization. This approach represents a new development that has not yet been empirically tested for its usefulness in predicting stock returns.

Two research questions are related to this aspect. First, Research Question 3 (RQ3) asks about the methods that are most suitable for investigating the role of investor sentiment in moderating the impact of exogenous shocks on stock prices. It was partially answered in Chapter 4.2, where the selection process of the most suitable approach to capture daily, firm-specific investor sentiment has already been described based on the specific requirements of this research framework. The second is Research Question 4 (RQ4) on whether an investor sentiment measured using a market-based approach is a reliable predictor of future security performance still needs to be investigated. Hypothesis H1 is the operationalization of RQ4, referring to the Overall Sentiment Indicator (OSI) and the daily returns of the S&P 500 index.

To assess the prediction accuracy of the weighted OSI for the daily returns of the S&P 500 Index between January 2nd, 2019, and April 30th, 2020, the non-parametric Spearman's rank correlation test was used in the first step to determine the correlation between the OSI and the S&P 500 Index daily returns (Table 14). Spearman's rank correlation test shows a significant correlation between the OSI values and the S&P 500 daily returns.

Table 14. Results of Spearman's Rank Correlation Test for the OSI and the S&P 500 Index daily returns

Spearman's ρ	Assymp. std. error	t-test	p-value
0.16	0.06	2.89	0.004***

Note: n=321.

Source: own compilation.

The next step is to use the Granger test for causality between the daily OSI values and the S&P 500 Index daily returns. First, the stationarity of the two variables is checked using the Augmented Dickey-Fuller test (Dickey & Fuller, 1979) (Table 15).

Table 15. Results of the Augmented Dickey-Fuller Test for OSI and S&P 500 Index daily returns

ADF (Augmented Dickey-Fuller Test for Stationarity)		
	OSI	**S&P 500 index daily returns**
Tau stat	-18.861	-45.286
Tau crit	-2.871	-2.871
Stationary	yes	yes
AIC	4.627	-4.912
BIC	4.650	-4.889
Lags	0	0
Coeff.	-1.060	-1.736
p-value	< 0.01	< 0.01

Source: own compilation.

The results show that both variables are stationary, which is the central requirement of Granger's causality test. Second, the number of lags with the highest goodness of fit is first determined using the Akaike criterion, Schwarz's Bayesian criterion, and the Hannan-Quinn criterion (Table 16).

Table 16. Determination of the Optimal Number of Lags for Granger's Test for Causality

Lags	Loglik	p(LR)	Akaike Criterion	Schwarz Bayesian Criterion	Hannan-Quinn Criterion
1	153.505	-	-0.949	-0.876*	-0.920
2	162.180	.002	-0.979	-0.858	-0.931
3	170.720	.002	-1.008	-0.839	-0.941
4	182.414	.000	-1.057	-0.841	-0.971
5	183.929	.553	-1.041	-0.777	-0.936
6	210.331	.000	-1.128	-0.815	-1.002
7	215.420	.000	-1.192	-0.832	-1.048
8	220.225	.050	-1.198	-0.789	-1.034
9	230.561	.000	-1.238	-0.781	-1.056*
10	235.899	.030	-1.247*	-0.742	-1.045

Note: asterisks indicate the minimized values of the respective information criteria.

Source: own compilation.

The Schwarz Bayesian criterion indicates a lag of 1 as the best-fitting to the model. In contrast, the Hannan-Quinn Criterion indicates 9 lags, and the Akaike Criterion 10 lags as the model with the highest goodness of fit. It can be assumed that the lowest possible lag tends to increase the probability of causality due to the reduced probability of the influence of other variables for shorter lags. The further calculation and test for Granger causality is thus carried out based on a lag of 1 (Tables 17 and 18). Two tests for Granger causality were conducted for $lag = 1$. One for daily OSI potentially affecting S&P 500 index daily returns (Table 17), and the second for S&P 500 index daily returns potentially affecting daily OSI (Table 18).

Table 17. Results of Test for Granger Causality between Daily OSI and S&P 500 Index Daily Returns (lag 1)

	Coefficient	Std. error	t-ratio	p-value
const	0.000	0.000	0.237	0.813
OSI	0.000	0.000	2.315	0.021**
S&P 500 index daily returns	-0.395	0.053	-7.436	0.000***
	F-test	P-value		
F(1, 317)	5.358	0.021**		

Source: own compilation.

Table 18. Results of Test for Granger Causality between S&P 500 Index Daily Returns and Daily OSI (lag 1)

	Coefficient	Std. error	t-ratio	p-value
const	0.009	0.134	0.065	0.948
OSI	0.913	0.023	40.100	0.000***
S&P 500 index daily returns	5.962	7.510	0.794	0.428
	F-test	P-value		
F(1, 317)	0.630	0.428		

Source: own compilation.

Significant Granger causality was found for the first direction of influence tested, for a $lag = 1$ (Table 17). Thus, the daily OSI values help forecast the S&P 500 index's daily returns. Regarding the inverse direction, Table 18 shows no significant Granger causality for $lag = 1$. So, the S&P 500 index's daily returns do not predict daily OSI values. Concluding, the results support the Predictive Hypothesis H1, stating that the OSI available on a daily basis, aggregated from data for companies included in the S&P 500 index, is capable of predicting the daily returns of the S&P 500 index.

6.2.2 Sentiment Indicator as a Predictor of Daily Stock Returns

In the first step, Spearman's rank correlation test to statistically analyze this hypothesis proved that the values of the sentiment indicator and the daily stock returns of the S&P 500 Index are correlated (Table 14). The correlation is positive, so an increase in the sentiment indicator's daily value also increases the daily stock returns. Furthermore, Granger’s test for causality shows that the daily OSI values Granger-cause the S&P 500 index daily returns (Table 17).

These findings show that there is an information flow between the two variables. Even if Granger's test for causality cannot prove “real” causality due to its limitations, there is more than just a simple correlation between the two variables. The weighting of companies based on their market capitalization thus proves to be a helpful aspect in the construction of precise sentiment indicators. At the same time, the significant result proves the suitability of an index-based approach for predicting stock returns, even in a period with potentially unexpected, shock-like events.

These results confirm the suitability of the approach proposed by Seok *et al.* (2019b), which was tested in the Korean markets in the past, also for a broader and more developed index such as the S&P 500. However, the results contrast with the findings of a study by Canbaş and Kandir (2009), who were unable to prove Granger-causality in an investigation of the causal relationship between investor sentiment and stock returns in the emerging market of Turkey, while finding that vice versa, stock portfolio returns, on the other hand, appear to influence investor sentiment.

To sum up, the Predictive Hypothesis (H1) stating that the Overall Sentiment Indicator available on a daily basis between January, 2nd, 2019, and April, 30th, 2020, aggregated from the companies included in the S&P 500 index, is capable of predicting the daily returns of the S&P 500 index, cannot be rejected. Investor sentiment can predict stock prices.

6.3 Exogenous Shock and Abnormal Returns

One aspect of Research Question 6 (RQ6) delves into how exogenous shocks, like the COVID-19 pandemic, impact stock prices across companies. To investigate this aspect and to answer RQ6, the first step is to test Return Hypotheses H2a, H2b, and H2c to check whether cumulative abnormal returns occurred for stocks of the companies examined during the events investigated, i.e., the first confirmed positive COVID-19 case in the US (H2a), declaration of the National Health Emergency (H2b) and declaration of the pandemic (H2c).

6.3.1 Abnormal Returns during the Defined Event Windows

All measured values and cumulative abnormal returns in this analysis were calculated based on the daily stock performance of individual companies, which have been aggregated subsequently to measure the statistical significance of the findings. Thus, results for individual companies may vary; though this study does not examine or address those differences in more detail.

The effect of information about COVID-19 on stock prices (abnormal returns) was tested using the test statistic of the Generalized Sign Test is calculated using the following formula:

$$Z = \frac{w - N \times \hat{p}}{\sqrt{N \times \hat{p}(1 - \hat{p})}}$$

where w is the number of positive $AR_{i,0}$ in the sample at the time of the event and $\hat{p}$ is the positive proportion of abnormal returns $AR_{i,t}$ in the observation window.

The results in 81 values for z statistics calculated for the 27 individual scenarios, distributed across the three panels (Table 19): symmetrical around each event day (panel 1), starting on the event date (panel 2), and beginning before the event and ending with the event date (panel 3) as described in Chapter 5.2.1.

Hypothesis H2a states that the disclosure of the first COVID-19 case in the US leads to negative abnormal returns on stocks of companies operating in the US and included in the S&P 500 index. Scenarios a-c are the corresponding scenarios in the overview. For none of these scenarios, significant results were found, so hypothesis H2a needs to be rejected.

Hypothesis H2b states that the declaration of the COVID-19 outbreak as a public health emergency in the US (American Hospital Association 2020) leads to negative abnormal returns on stocks of companies operating in the US and included in the S&P 500 index. So, it refers to January 31st, 2020, and scenarios d-f are the corresponding scenarios in the overview. The test statistics show mixed results for this date. In panel 1, significant CARs can be found for five trading days and seven trading days around January 31st, 2020. In panel 2, three, five, and seven trading days after January 31st, 2020, show significant results. In the case of panel 3, only the periods of three and seven trading days before the event show significant results, confirming the occurrence of CARs during these periods. Overall, the findings support hypothesis H2b, although further differentiation and interpretation of the results is necessary (Chapter 6.3.2).

Table 19. Effect of Information about COVID-19 on Stock Prices

Scenario	Date (Length of Event Window in Trading Days)	Z	p-value	Significance
		Panel 1		
a1	21.01.2020 (3)	-1.041	0.149	
b1	21.01.2020 (5)	0.534	0.703	
c1	21.01.2020 (7)	-1.041	0.149	
d1	31.01.2020 (3)	-1.146	0.126	
e1	31.01.2020 (5)	-3.875	0.000	***
f1	31.01.2020 (7)	-2.825	0.002	***
g1	11.03.2020 (3)	-4.295	0.000	***
h1	11.03.2020 (5)	-8.809	0.000	***
i1	11.03.2020 (7)	-6.605	0.000	***
		Panel 2		
a2	21.01.2020 (3)	1.164	0.878	
b2	21.01.2020 (5)	0.429	0.666	
c2	21.01.2020 (7)	-1.566	0.059	
d2	31.01.2020 (3)	-3.035	0.001	***
e2	31.01.2020 (5)	-4.925	0.000	***
f2	31.01.2020 (7)	-5.450	0.000	***
g2	11.03.2020 (3)	-8.180	0.000	***
h2	11.03.2020 (5)	-6.815	0.000	***
i2	11.03.2020 (7)	-7.025	0.000	***
		Panel 3		
a3	21.01.2020 (3)	-0.411	0.341	
b3	21.01.2020 (5)	0.010	0.504	
c3	21.01.2020 (7)	-1.041	0.149	
d3	31.01.2020 (3)	-2.930	0.002	***
e3	31.01.2020 (5)	-0.936	0.175	
f3	31.01.2020 (7)	-2.300	0.011	**
g3	11.03.2020 (3)	-5.345	0.000	***
h3	11.03.2020 (5)	-5.240	0.000	***
i3	11.03.2020 (7)	-3.875	0.000	***

Source: own compilation.

Hypothesis H2c states that the WHO's declaration of a pandemic leads to negative abnormal returns on stocks of companies included in the S&P 500 index. So, it focuses on March 11th, 2020, as the event date. For this event date, every scenario (g-i) showed significant results, meaning that for every investigated period and every panel, CARs occurred and were significant. Finally, the results support hypothesis H2c.

6.3.2 Understanding the Effect of COVID-19 on Stock Prices

The statistical analysis relating to hypothesis H2a, referring to the disclosure of the first COVID-19 case, shows no significant results; the occurrence of CARs can, therefore, not be proven based on the study panels for January 21st, 2020 (Table 19). Hypothesis H2a must, therefore, be rejected. One explanation for the findings may be the course of infection during the COVID-19 outbreak. When looking at January 21st, it must be taken into account that although the virus had already reached several countries by this date, more than 95% of infections were registered in China at the same time. The case confirmed in the US was even the first outside Asia (WHO, 2020). Since even the period immediately before the event examined as part of panel 3 did not show any significant (negative or positive) cumulative abnormal returns either (Table 19), this indicates that the event might not be considered sufficiently significant by market participants or as a somewhat local phenomenon similar to the spread of Ebola. The endemic spread of Ebola is predominantly limited to the African continent, as the incubation time of the disease is so short and the mortality rate is so high that most infected patients die before further infections can occur over a greater distance (Huber *et al.*, 2018). A second explanation could be investors' earlier anticipation of the event, leading to the fact that the event had been priced earlier. Investors had to assume that it was only a matter of time before the virus reached other countries, such as the US. Both explanations, although contradictory, seem conceivable in this case. A third aspect that could explain the lack of an abnormal reaction and adaptation of investors’ expectations could be the fact that it was only two days later that a country (in this case, China) took concrete, restrictive measures ("lockdown") for the first time. Until this point, it is possible that the specific economic effects and implications of the spread of COVID-19 to the US were not yet visible or assessable enough to determine a measurable reaction from market participants around January 21st. To summarize the findings on January 21st, it can be stated that the effects of an event (regardless of whether they will occur or are merely speculation) must be sufficiently concrete to trigger a measurable short-term reaction from market participants.

The results for the second observation date, January 31st, 2020, vary by scenario (Table 19). In Panel 1, analyzing a symmetrical number of trading days around the event date, significant results can only be found in the observation windows of five (-2,+2) and seven trading days (-3,+3) around the event. Panel 2, focusing on the occurrence of CARs strictly after the event date, shows significance for three (0,+2), five (0,+4), and seven trading days (0,+6) periods. Panel 3, focused on anticipatory effects, reveals significance for the (-2,0) window and for the (-6,0) window. These results suggest that the US health authorities' declaration of a national health emergency was largely unexpected, causing abnormal returns as investors adapted their expectations based on the news, particularly in the days surrounding and following the event.

Finally, all panels and scenarios examined around the event date of March 11th, 2020, show highly significant results, confirming that the declaration of COVID-19 as a global pandemic by the WHO had a significant impact on S&P 500 stock prices both before and after the event, leading to irrational, cumulative abnormal returns (Table 19). By this time, COVID-19 had already spread widely, and to many countries globally, initial restrictions had been put in place. The pandemic declaration made it clear to market participants that the outbreak was not short-term or local and that S&P 500 companies would likely be affected by future measures, solidifying investor uncertainty.

Regarding hypotheses H2a, H2b, and H2c, cumulative abnormal returns were detected for most scenarios and for the dates of January 31st and March 11th, 2020. This is in line with the results of Chau *et al.* (2016), who found that sentiment is a relevant factor in stock price variations for US stocks, and various other studies suggesting a significant impact of COVID-19-related events on US stock prices and the S&P 500 index, in particular in March 2020 (Chapter 2.4). The results show that investors faced an unexpected, exogenous shock on January 31st and March 11th, 2020, resulting in more emotional behavior. January 21th, however, cannot be considered a “shocking” event. To analyze the strength of impact for the three events, the z-values, indicating the magnitude and direction of the difference from the comparison period, can be analyzed (Table 19).

The obtained values show that the direction is negative for the significant event dates. For January 31st, 2020, in particular, a comparison of the respective scenarios (scenarios d2, e2, and f2 in comparison to scenarios d3, e3, and f3) in panel 2 and panel 3 clearly shows that the event's negative impact on stock returns is significantly greater and more visible after the event than immediately before the event. This indicates that there were fewer anticipatory effects on this day than on the other dates examined and that this event was actually unexpected for many market participants. Differences in the magnitude of the effects identified between panels 2 and 3 can also be demonstrated for March 11th, 2020, but these are not as clear as they were for January 31st, 2020.

Furthermore, the effect's overall magnitude increases from event to event. Research Question 8 (RQ8) focuses on this aspect, asking about identifiable patterns in how investors respond to a series of shock events. Unlike studies suggesting that repeated shocks being linked to the same overarching situation (e.g., in the case of wars) lead to more rational markets and thus weaker responses (corresponding to lower or no CARs) over time (Peleg *et al.*, 2013), this study indicates that the accumulation of COVID-19-related events increased the impact of behavioral or even emotional factors, resulting in higher CARs.

Investor action seemed to be driven by "dwindling optimism". Early in the pandemic, optimism persisted despite concern. However, as the virus spread and the number of infections grew, particularly by March 2020, when the pandemic was officially declared, hopes for a quick recovery faded. This led to further sell-offs, shifting from rational to more emotional responses. This development fits well with the observations on the course of the OSI (Chapter 6.1), which shows decreasing sentiment values from event to event. The compounding nature of these events, rather than isolated reactions, suggests that future behavioral finance research should consider how linked events influence investor behavior. In summary, it can be stated that hypothesis H2a cannot be supported in the present study, while hypotheses H2b (partly with differentiation) and H2c are supported by findings.

6.4 Exogenous Shock and Stock Price Company-Specific Volatility

This section deals in particular with the development of volatility in the period under review. This aligns with one of the aspects of Research Question 6 (RQ6), asking how exogenous shocks, like the COVID-19 pandemic, impact stock price volatility across companies. The hypotheses referring to this problem are H3a, H3b, H3c (Chapter 3.3). They state that the analyzed events affect stock price volatility for companies operating in the US and included in the S&P 500 index. H3a refers to the event of disclosure of the first COVID-19 case in the US. H3b refers to the declaration of the COVID outbreak as a public health emergency in the US by the American Hospital Association in 2020, and H3c to the World Health Organization's declaration of the pandemic. They focus on measuring significant deviations from "normal" volatility behavior, which in the present study is characterized by the comparison period starting on January 2nd, 2019, and ending on the respective event date.

The calculation and testing of the model are carried out (as described in Chapter 5) based on two test procedures. First, the "classic" cross-sectional test statistics recommended for event studies by Brown and Warner (1980) will be calculated to check for abnormal volatilities. Second, a modified and more suitable version of the cross-sectional t-statistics for event studies, as proposed by Savickas and Balaban (2006) based on an approach by Savickas (2003), will be used. The test results for the widely used cross-sectional test statistic according to Brown and Warner (1980) are presented in Table 20.

Table 20. Cross-Sectional t-Statistics Based on Brown & Warner (1980) for Company-Specific Volatility

Event Date	21.01.2020	31.01.2020	11.03.2020
$test_1\ (\hat{\gamma})$	-2.255	-0.999	-2.000
p-value	0.031**	0.242	0.054*

Note: n=360.

Source: own compilation.

In the case of the first event (21.01.2020), when using the unstandardized gamma values based on the normal cross-sectional t-statistics as suggested for an event study by Brown & Warner (1980), the result was found significant at the $\alpha = 0.05$ level. For the second event date, 31.01.2020, the cross-sectional t-test shows no significance. For the event date of the declaration of the COVID-19 outbreak as a global pandemic (11.03.2020), the result was found significant at the $\alpha = 0.1$ level.

The results obtained using the procedure according to Savickas (2003) and Balaban and Constantinou (2006) are presented in Table 21.

Table 21. Cross-Sectional t-Statistics Based on Balaban & Constantinou (2006) for Company-Specific Volatility

Event Date	21.01.2020	31.01.2020	11.03.2020
$test_2\ (\hat{\gamma})$	1.187	-1.000	-1.054
p-value	0.197	0.242	0.229

Notes: n=360.

Source: own compilation.

None of the tests based on this "standardized" approach showed significant results. As described in Chapter 4, the results of $test_2$ are decisive for the investigation of hypotheses H3a, H3b, and H3c due to the stronger consideration of the company-specific reaction to the respective events. Test 2 shows no significant results in each case, though hypotheses H3a, H3b, and H3c are therefore rejected. As part of the interpretation of the results in Chapter 6.4.2, the test results will be discussed in more detail.

Based on the significance test by Savickas (2003) and Balaban & Constantinou (2006), taking into account the normalization by company-specific and event-induced conditional standard deviation, abnormal volatility development could not be demonstrated for the present sample for any of the events Using the "simple" cross-sectional test statistics, however, significant results were found for January 21^{st}, 2020, and March 11^{th}, 2020.

The results initially appear counterintuitive, mainly because several studies have demonstrated the impact of uncertainty on volatility in general (Su *et al.*, 2019; Asgharian *et al.*, 2023) and in the case of the COVID-19 outbreak in particular. The findings in this study seem inconsistent with those of previous research. Numerous studies have demonstrated the influence of COVID-19-related news and events (Baek *et al.*, 2020; Baker *et al.*, 2020; Chaudhary *et al.*, 2020; Haroon & Rivzi, 2020; Zaremba *et al.*, 2020; Zhang *et al.*, 2020; John & Li, 2021) and other factors, such as positive cases or deaths (Chowdhury *et al.*, 2022) in the wake of COVID-19, on stock price volatility, mainly showing a vast increase in the volatility levels. In summary, volatility tends to increase when the market environment shows increased ambiguity, with many market participants developing negative expectations about the future. In contrast, other market participants see the same situation as an opportunity for gains and, therefore, as a buying opportunity, both impacting the volatility of securities.

A closer look reveals an explanation for the differing results. First, this dissertation deals with the effects of three particular events on the company-specific volatility of the companies in the sample, unlike other studies, focusing on the general influence of variables such as confirmed cases or generally “the outbreak of COVID-19” on the volatility development of a market. Beak *et al.* (2020) apply a Markov Switching AR Model, which is not linked to the impact of a specific event, to the overall market volatility in the wake of the COVID-19 outbreak. Baker *et al.* (2020) use a newspaper-based Equity Market Volatility Tracker, matching it to the VIX index to determine the effect of COVID-19 on the overall market volatility. Zhang *et al.* (2020) compare different country indices' volatility from February 2020 to March 2020 and perform a correlation analysis to find underlying connections and patterns. Zaremba *et al.* (2020) use regression to measure the impact of government interventions on stock price volatility in different countries based on interventions’ stringency. John and Li (2021) investigate the effects of, besides others, the COVID-19 index on the jump component of the VIX index in the ten days between January 21st and January 31st, 2020.

Furthermore, this study considers company-specific factors, which have been largely ignored for volatility analysis during the COVID-19 pandemic. In particular, the effect of company-specific conditional standard deviation as a standardizing element for event-induced volatility has not been considered by any study to date (as far as is known).

Even though Haroon and Rivzi (2020) use an EGARCH model, considering conditional variance, followed by an OLS regression to determine the impact of news sentiment on volatility, their investigation focuses on world and US indices. Chaudhury *et al.* (2020) apply a GARCH model, which also considers conditional variance, extend it by a COVID-19 dummy variable, but do not focus on specific events, and rather differ the non-COVID-19 period from the COVID-19 period (January 1st, 2020, to June 30th, 2020). They investigate ten market indices of various countries.

In summary, the studies and results published to date are not exactly comparable with the results of this dissertation, mainly due to a different focus and research design. Previous studies have mainly focused on the impact of COVID-19 on the volatility of broad country and market indices without focusing on company-specific factors. The research methodologies used only partially or indirectly take into account company-specific conditional or event-induced volatility.

Based on the “standard” cross-sectional test statistics, the results of the other studies are reflected. They show significant results for two of the three events examined (January 21st and March 11th, 2020) (without considering the effects of the events examined on company-specific volatility). However, this result cannot be confirmed at the company-specific level in the current dissertation.

Regarding Research Question 6 (RQ6), the results of this study reveal that the three exogenous shocks do not impact stock price volatility at the company-specific level. In turn, and given previous research and the (partially) significant results of the cross-sectional test statistics, it can be assumed that not a specific event or a specific new piece of information but the generally increased uncertainty leads to a change in volatility in the wake of COVID-19. No significant effects can be measured considering a company-specific development of the standard deviation. Thus, the Volatility Hypotheses (H3a, H3b, and H3c) are not supported by the results of this study either.

In addition, the obtained result provides two critical implications for further research: First, future studies should incorporate the firm-specific perspective more firmly in their considerations, as a pure focus on broad indices may lead to misleading results. Second, it shows that analyzing volatility is a complex challenge that can lead to different implications depending on the chosen research design.

6.5 Moderating Role of Investor Sentiment During Exogenous Shock

The following section deals with investor sentiment and its moderating role in connection with the events under consideration and the development of the share prices examined.

The investigation of the moderating role of investor sentiment in the occurrence of CARs following the events investigated during the COVID-19 spread is based on hypotheses H4a, H4b, and H4c, stating that investor sentiment moderates the relationship between a given release of information and the stock prices of companies operating in the US and included in the S&P 500 index. These hypotheses are linked to Research Question 7 (RQ7), investigating the role of investor sentiment in stock prices’ changes during the COVID-19 pandemic outbreak. The focus here is on whether positive (negative) sentiment has a dampening (reinforcing) effect on the share price performance of the companies examined. asking about the role of investor sentiment in stock prices’ changes during the COVID-19 pandemic outbreak.

The different examination scenarios include different classification logics for categorizing the examined companies into high, medium, and low sentiment, as well as different lengths and positions of the event window compared to the respective event date. The significance tests (the Mann-Whitney test and the Median test) were calculated for the 81 scenarios as presented in Tables 22 and 23. The results show that for the event dated January 21st, 2020, findings support hypothesis H4a and, thus, investor sentiment moderates the relationship between the release of information about the first COVID-19 case, and the stock prices of companies operating in the US and included in the S&P 500 index. In the case of January 31st, 2020, which is related to hypothesis H4b, results are significant around the event date (panel 1) except for means for individual companies in the 7-day event window. Regarding the effect starting on the event date (panel 2), the results were found significant for all methods only in the case of the 7-day windows. In the window before the event, all the results were significant. For March 11th, 2020, the results vary depending on the observation period under consideration, with 20 out of 27 scenarios confirming significant differences between the "sentiment groups". In total, the findings support hypothesis H4c. In other words, investor sentiment moderates the relationship between the release of information about the declaration of the pandemic by the WHO and the stock prices of companies operating in the US and included in the S&P 500 index. The detailed implications of the results and the differences between the differentiation methods used to form the ordinal sentiment clusters are explained further in the interpretation of the results.

Not all hypotheses were confirmed, while others showed significant results. Given the overall results of the statistical analyses, it can be stated that investor sentiment plays a moderating role in the wake of the investigated events, even if further distinctions and further investigations are necessary in detail. The results suggest, after considering the direction and strength of the test results of the Mann-Whitney U test (Table 22), that the companies in the "high" sentiment group immediately before the event show significantly lower (cumulative) abnormal returns than the companies in the "low sentiment" group. This observation can be largely confirmed for all event data and all classification logic used, with a few exceptions in individual measurement combinations. Overall, the results thus support the Moderating Effect Hypotheses (H4a, H4b, and H4c).

Table 22. Mann-Whitney U Test Results for Different Scenarios

Scenario	Date (Length of Event Window in Trading Days)	Cross-Sectional Mean	Cross-Sectional Median	Mean of Individual Company
Panel 1				
a1	21.01.2020 (3)	-7.686***	-7.490***	-7.920***
b1	21.01.2020 (5)	-7.676***	-7.428***	-8.211***
c1	21.01.2020 (7)	-9.081***	-9.187***	-9.880***
d1	31.01.2020 (3)	-5.845***	-5.767***	-5.702***
e1	31.01.2020 (5)	-5.497***	-5.761***	-5.154***
f1	31.01.2020 (7)	-3.012***	-3.848***	-3.107***
g1	11.03.2020 (3)	-1.584	-1.558	-1.050
h1	11.03.2020 (5)	-5.880***	-6.121***	-1.576
i1	11.03.2020 (7)	-5.244***	-5.420***	-3.627***
Panel 2				
a2	21.01.2020 (3)	-6.372***	-6.046***	-7.099***
b2	21.01.2020 (5)	-7.753***	-7.929***	-8.443***
c2	21.01.2020 (7)	-7.280***	-7.590***	-7.739***
d2	31.01.2020 (3)	-0.794	-1.064	-0.263
e2	31.01.2020 (5)	0.810	0.508	1.089
f2	31.01.2020 (7)	-3.261***	-3.627***	-2.689***
g2	11.03.2020 (3)	-2.245**	-2.395**	-2.366**
h2	11.03.2020 (5)	-5.485***	-5.410***	-4.082***
i2	11.03.2020 (7)	-1.433	-1.540	-3.114***
Panel 3				
a3	21.01.2020 (3)	-9.604***	-9.398***	-9.612***
b3	21.01.2020 (5)	-10.498***	-10.667***	-10.458***
c3	21.01.2020 (7)	-11.701***	-11.661***	-11.588***
d3	31.01.2020 (3)	-7.818***	-7.718***	-7.675***
e3	31.01.2020 (5)	-9.641***	-9.963***	-9.612***
f3	31.01.2020 (7)	-12.864***	-12.874***	-12.330***
g3	11.03.2020 (3)	-7.126***	-7.126***	-1.479
h3	11.03.2020 (5)	-8.169***	-8.642***	-8.169***
i3	11.03.2020 (7)	-11.354***	-11.747***	-3.347***

Source: own compilation.

Table 23. Median Test Results for Different Scenarios

Scenario	Date (Length of Event Window in Trading Days)	Cross-Sectional Mean	Cross-Sectional Median	Mean of Individual Company
Panel 1				
a1	21.01.2020 (3)	51.171***	46.691***	51.645***
b1	21.01.2020 (5)	42.539***	38.469***	51.645***
c1	21.01.2020 (7)	60.600***	65.522***	75.483***
d1	31.01.2020 (3)	32.444***	28.744***	24.560***
e1	31.01.2020 (5)	30.085***	28.744***	7.307***
f1	31.01.2020 (7)	4.451**	34.302***	-1.584
g1	11.03.2020 (3)	0.011	0.011	1.026
h1	11.03.2020 (5)	28.828***	31.039***	2.849*
i1	11.03.2020 (7)	16.858***	18.575***	9.229***
Panel 2				
a2	21.01.2020 (3)	29.923***	26.534***	37.379***
b2	21.01.2020 (5)	51.151***	58.891***	57.996***
c2	21.01.2020 (7)	51.171***	58.891**	54.775***
d2	31.01.2020 (3)	0.712	0.895	0.0507
e2	31.01.2020 (5)	1.602	0.895	5.074**
f2	31.01.2020 (7)	4.451**	5.846**	4.110**
g2	11.03.2020 (3)	4.001**	4.873**	5.583**
h2	11.03.2020 (5)	18.632***	18.575***	5.583**
i2	11.03.2020 (7)	1.341	1.337	9.230***
Panel 3				
a3	21.01.2020 (3)	67.327***	65.522***	61.309***
b3	21.01.2020 (5)	97.781***	103.980***	103.831***
c3	21.01.2020 (7)	115.134***	117.241***	112.759***
d3	31.01.2020 (3)	57.677***	55.709***	51.961***
e3	31.01.2020 (5)	60.927***	68.970***	65.763***
f3	31.01.2020 (7)	134.626***	141.111***	116.912***
g3	11.03.2020 (3)	31.134***	35.901***	2.849*
h3	11.03.2020 (5)	49.754***	54.104***	5.723**
i3	11.03.2020 (7)	117.585***	126.508***	5.583**

Source: own compilation.

Concerning the various panels and their design, it can also be deduced from the results that the events examined were predominantly already anticipated. The results of Return Hypotheses H2a, H2b, and H2c provide the concrete indication that cumulative abnormal returns occurred in the context of the events (except January 21st, 2020), the differences between the companies with high and low investor sentiment, even for the observation periods prior to the events, are clearly documented.

Following the analysis of the significant and insignificant effects of exogenous shocks on stock prices using the GARCH (1,1) model, the results indicate that for the first event, 71.5% of the dummy variables were significant, while 28.5% were not. For the second event, 51.4% were significant and 48.6% insignificant, and for the third event, 35.8% were significant compared to 64.2% insignificant. These findings suggest a declining influence of external shocks related to COVID-19 over time, likely due to increased availability of information about the pandemic.

Table 24 presents the results of the Chi-square test of independence, which evaluated the variation in stock price responses to external shocks between companies with high IS and those with low IS. Although differences in CARs were observed, the Chi-square tests revealed no statistically significant difference in the stock price responses between the two groups.

Table 24. Differences in impact significance for S&P 500 companies with high/low IS

	P1_mean		**P1_median**		**P2_mean**		**P2_median**		**P3_mean**		**P3_median**	
No.	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Signific.	139	117	120	136	102	82	86	98	74	54	67	61
Insignific.	60	42	52	50	97	77	86	88	125	105	105	125
Statistic	0.61		0.49		0.00		0.26		0.40		1.48	
p-value	0.44		0.48		0.95		0.61		0.53		0.22	

Notes: P1 (P2, P3) – refers to event date, specifically 21.01.2020 (31.01.2020, 11.03.2020), mean(median) – high IS defined as higher than the cross-sectional mean (median).

Source: own compilation.

Two different theories can be considered to explain these results, which are based on the question of the rationality of the investor reaction as a central distinguishing feature. Firstly, the companies with high sentiment were conceivable to be subject to a “protective mechanism”. Since, by definition, shock situations occur unexpectedly and investors react to negative news, in particular with overreactions (Barberis *et al.*, 1998), it can be deduced that a short-term reaction of market participants to the event is to be regarded as emotional rather than rational. Suppose the reaction of market participants is emotional. In that case, they will react to the news in a panic and possibly be driven by herd behavior (as described, i.e., by Bouri *et al.*, 2021) and thus want to sell their securities, resulting in falling stock prices. Their behavior is additionally reinforced by the negativity effect described by Baumeister *et al.* (2001), according to which investors react more strongly to extremely negative news than to positive news. At the same time, however, they will be unable to adjust their sentiment towards the individual companies in the short term. Hence, the sentiment set for a company immediately before the event occurs remains unconsciously valid.

Although there is a broad sell-off of stock due to the nature of the event, the positive sentiment towards the companies helps to “protect” them, leading to lower negative abnormal returns and reducing selling pressure compared to those companies with lower sentiment. In other words, positive sentiment seems to shield companies from uncertainty-driven price swings.

This explanation could relate well to previous findings on the influence of investor sentiment on the risk-reward relationship. The COVID-19 spread increased uncertainty in the market and the downside potential for individual securities. As discussed in Chapter 6.4, this leads to an overall increase in volatility in the stock markets, even if this increase was not entirely attributable to the events investigated in this dissertation (Chapter 6.4). This increase in uncertainty and volatility will likely result in a higher risk for market participants, which should be reflected in a higher risk premium based on a positive risk-reward relationship. The present results show that the risk-reward relationship developed differently depending on investor sentiment. A less pronounced fall in stock prices for companies in the “high sentiment” group indicates that more investors are prepared to continue holding or buying the securities despite the increased risk. This difference can be explained by a different, irrational perception of sentiment-driven investors. This is in line with the findings of Seok *et al.* (2024), showing that firm-specific investor sentiment positively impacts stock returns, particularly when uncertainty increases. Another interesting contribution from Pandey *et al.* (2024) found that markets in countries with a higher level of population "happiness" seem to be less affected by tragic events, also showcasing the impacting and "protective" role of positive sentiment in a different setup.

However, an alternative to this explanation could be a rational reaction on the part of investors. Up until some years ago, it was not even conceivable that a sentiment-driven reaction of investors could be seen as rational. This changed with recent investigations (Chau *et al.* 2016, Ahmed, 2020), which focused particularly on the distinction between sentiment-driven reactions into rational and irrational portions.

On the one hand, Soros (1987) already proved that sentiment-driven investors actively trade against the herd when sentiment is low and prices fall as a result. He explains this by a rational evaluation of the situation including a transparent knowledge about the sentiment, leading to perceived buying opportunities for investors. Based on this study, Chau *et al.* (2016) added two further findings. Firstly, they investigated the impact of three groups of traders, the "rational utility maximizers, also called "smart money investors", the positive feedback traders, and the sentiment-driven investors on the US stock prices. They proved that sentiment-driven investors trade more aggressively in times of bearish, low market sentiment than in times of increasingly positive sentiment. Secondly, by applying their research methodology to the S&P 500 Index and the DJIA, they proved that sentiment-driven traders behave like so-called contrarians, i.e., buy consciously and out of a rational profit motive when most market participants are selling. A further study confirmed these findings (Ahmed, 2020).

The results of these studies could also apply to the results of this study. If the investors did act rationally, like sentiment-driven contrarians following the investigated events, they bought aggressively and out of rational interest, while the shocks resulted in panic-like sell-offs in the market as a whole. The sell-offs have been evidenced by significantly negative CARs. Chau *et al.* (2016) explained this behavior, similar to Soros (1987), by referring to psychological effects known to sentiment-driven traders. Based on the mentioned negativity bias, bad news leads to a more extreme reaction by investors. Possibly, this could be seen as a good buying opportunity for the group of sentiment-driven traders. In the study of Chau *et al.* (2016) and the present investigation, investors preferred buying stock from companies whose sentiment was already positive. The shock led to falling stock prices, although these were lower for securities with positive sentiment as a result of the additional purchases and possibly stronger holding of the shares compared to shares in the "low stock prices" group.

In comparing the two explanatory variants, the occurrence of emotional, sentiment-driven behavior nevertheless seems more likely than the theory of rational "contrarian"-like behavior in the current research framework. Based on previous research, the assumption that the investors did not act rationally after such unexpected shocks and that the "protective mechanism" for stocks with positive sentiment came about unconsciously seems more likely and conceivable. Also, in the current study, there are hints that for non-anticipated shocks, investors' negative, abnormal reaction is pronounced stronger than for partially anticipated situations. The investors react in the truest sense of the word "shocked". However, further research should focus on whether sentiment-driven investors act rationally or emotionally during exogenous shocks with their sudden and unexpected character.

CHAPTER 7
CONCLUSIONS AND LIMITATIONS

This chapter summarizes the key findings of the dissertation. The research questions formulated in Chapter 2 are first answered based on the results of the statistical study (Chapter 6) and the subsequent interpretation. This is followed by a summary of the new research approaches in this dissertation that have not been previously addressed in this form.

The remainder of the chapter discusses the implications of the findings for further research as well as for practical application in the economic context. Finally, the limitations of the study are described, and a final summary is drawn.

7.1 Summary of Findings and Implications

As described in Chapter 1, this dissertation is based on various research questions that previous research and literature have not sufficiently answered. The primary aim of the study was to deepen the understanding of the role of company-specific investor sentiment in moderating the impact of exogenous shocks on stock prices. Thus, the results of this study can provide important implications for further research and investors in the stock markets.

In the first step, the theoretical foundations were described in the context of the aim of the dissertation (RQ1). Subsequently, the current study results were presented (RQ2), on the basis of which the hypotheses of this dissertation were derived in a further step.

Subsequently, the approach to measuring investor sentiment on a daily and company-specific level based on financial market indicators, developed by Seok *et al.* (2019b), was tested for its applicability in the context of the S&P 500 index. The indicator was selected following a detailed literature review of existing sentiment measures and research results. Research Question 3, asking how investor sentiment can be measured daily and at a company-specific level, and what methods or indicators best capture its nuances, has been answered thoroughly in Chapter 2, Chapter 4.1, and Chapter 4.2.

To investigate the prediction accuracy of the sentiment indicator, the values obtained for the individual companies in the sample were aggregated into the Overall Sentiment

Indicator (OSI) based on their market capitalization, which is a new approach to building an aggregated version of a sentiment indicator out of company-specific values that has never been tested empirically before. It was shown that the calculation methodology is valid as the obtained values significantly Granger-cause the daily returns of the S&P 500 Index while confirming previous research on the validity of the sentiment indicator itself in a new context. Research Question 4, asking whether a market-based approach to measuring investor sentiment can serve as a reliable predictor of future stock performance, can be answered positively. Both, correlation and Granger-causality to S&P 500 index daily returns have been empirically tested and proven to be statistically significant. However, for the reverse relationship, the Granger causality was not proven.

Research Question 5 referred to the question of how IS can be appropriately measured in the context of this study. Chapter 4.2.1 describes which characteristics an operationalization of the measurement of IS must fulfil for the current study. Subsequently, a suitable method is derived on the basis of the approaches presented in Chapter 4.1

Research Question 6 was about the impact of exogenous shocks, like the COVID-19 pandemic, on investor sentiment, stock prices, and stock price volatility across companies and sectors. In order to answer this question, several investigation steps have been conducted. The OSI and 11 sectoral indices were aggregated in the first step from the company-specific sentiment values. These were then examined visually and based on statistical data. This revealed that investor sentiment fell to its lowest levels in all sectors between February and April 2020, showing decreases in investor sentiment compared to the same period of the previous year. Individual sectors, such as the Energy and Utilities sectors, showed conspicuous downward trends in the first months of 2020, which can be explained by COVID-19-related micro- and macroeconomic changes. A comparison of the OSI with the Daily News Sentiment Index also shows differences, particularly in the period from February 2020. The question remains as to what the differences are due to and which of the two indicators has a higher correlation to the development of the prices of, for example, the S&P 500 index. The key finding of the dissertation is that investor sentiment is negatively influenced by exogenous shock situations, with differences in the intensity of the influence depending on the sector. The approach used, therefore, reflects the “shock” of market participants in the truest sense of the word. In the subsequent discussion of the results, arguments were found that provide a conclusive explanation for the development of the sentiment over time and, in particular, the divergent developments in investor sentiment between the sectors observed. However, the development of sentiment was not analyzed in more detail in this dissertation through a deeper analysis of the various sub-indicators. Other studies have already indicated which factors play a role in forming sentiment following shock situations (e.g., Carter & Simkins, 2004). Further research could provide even deeper insights here to better explain the emergence and development of sentiment in the future, particularly as a result of exogenous shocks.

In a second step, other studies' findings confirmed that two events under consideration also resulted in cumulative abnormal returns for the individual companies included in the S&P 500 Index. However, this dissertation also concludes that the first confirmed positive COVID-19 case in the US on January 21st, 2020, did not represent an exogenous shock situation for market participants, resulting in no observable CARs for this specific event. At the same time, however, it was also possible to prove that the other two events, despite showing negative CARs, had already been anticipated by some investors, leading to anticipatory negative CARs before the event dates.

In addition to the effects of the shock situations on the stock prices, the effects on volatility were also examined in more detail. It was shown that during the COVID-19 outbreak, volatility increased compared to “normal” times, but only for the whole sample and not when considering company- and event-specific factors. Thus, the results of this dissertation also require more detailed analysis. Although the discussion already brought up initial approaches, future research should investigate why no significant results were obtained using the cross-sectional t-test with standardized values based on company-specific and event-induced volatility. The use of a more far-reaching approach may provide further insights here. Already, the findings have implications for investors as well, as understanding the drivers of stock market volatility is crucial for risk management and portfolio allocation.

This dissertation also offers implications for the assessment of the COVID-19 pandemic as a whole, consisting of a sequence of several major or minor shocks, which corresponds to Research Question 8. The results suggest that uncertainty increased as the pandemic progressed and became more widespread, leading to ever-stronger negative bursts in sentiment and ever-larger CARs. This pattern, indicating the “dwindling optimism” of market participants, along with whether this finding is based on the decreasing sentiment levels or whether the events’ effects “stack” over time, also requires attention by future research. Oler, Harrison, and Allen (2008) argue that, particularly in the case of complex events whose effects are not fully known immediately or whose effects cannot be fully understood by market participants, the effects of a specific event only really become visible over a more extended period. The effects of the events investigated can be described as complex, so further research should be conducted in this direction, e.g., by expanding event and observation windows.

Finally, the question of what role investor sentiment plays in the price development of securities before and after the exogenous shock in the wake of the spread of COVID-19 has been investigated (Research Question 7). The research framework in this dissertation represents a new approach that has not previously been carried out in a comparable form and level of detail for the COVID-19 pandemic (Research Question 6). Based on different classification logics for "high", "medium", and "low" investor sentiment and different research scenarios, this study was able to provide comprehensive evidence that investor sentiment does indeed play a relevant role in the occurrence of cumulative abnormal returns during the investigated events. In most of the study scenarios, CARs were lower for companies with higher sentiment than those with lower sentiment. This finding has far-reaching implications, as it enables investors to systematically reduce their risks when exogenous shocks occur by systematically assessing the sentiment of companies and allocating their portfolios accordingly. However, the results also provide approaches for further research. For example, it is worth analyzing the phenomenon of investor sentiment in more detail in connection with whether the strength and not just the direction of investor sentiment also allows conclusions to be drawn about the formation of CARs.

Concluding, the findings of this dissertation hold significant theoretical, methodological, and practical implications. Regarding **theoretical implications**, the study advances the field of behavioral finance by deepening the understanding of how company-specific investor sentiment moderates the effects of exogenous shocks on stock prices, thereby extending existing sentiment theories to a new empirical context. **Methodologically**, it validates and refines the applicability of the Seok *et al.* (2019b) sentiment indicator for daily, firm-level measurement within the S&P 500, while introducing an innovative approach to aggregating company-specific sentiment values into an Overall Sentiment Indicator (OSI) based on market capitalization—a contribution that offers a replicable framework for future sentiment research. **Practically**, the results provide actionable insights for investors and financial analysts, demonstrating that sentiment dynamics can serve as early indicators of market vulnerability during crisis periods such as the COVID-19 pandemic. This enables more informed risk management, portfolio allocation, and strategic decision-making under conditions of uncertainty. Collectively, these implications underscore the importance of incorporating behavioral factors into traditional financial models and pave the way for further exploration of sentiment-based prediction and shock-response mechanisms in financial markets.

7.2 Originality of the Dissertation

This dissertation adds some relevant aspects to previous research— both on the influence of exogenous shocks in general and COVID-19 in particular, as well as on the role of investor sentiment and its influence on stock prices and stock volatility.

First, the consideration of company-specific factors in the determination of investor sentiment is not a unique feature of this dissertation. However, the subsequent aggregation of the individual company values in conjunction with a weighting based on market capitalization to form an overall sentiment indicator (in the case of the dissertation carried out for the broad market index S&P 500 as an example) is a unique selling point of this dissertation. The proof of the suitability of this aggregation method for future research is provided in the dissertation by demonstrating Granger-causality between the OSI and the development of the S&P 500 Index.

Another unique feature of the dissertation is the direct comparison of different relevant event dates in the context of the outbreak of the COVID-19 pandemic as well as a combined consideration of the various dates in the temporal course of the COVID-19 outbreak. Previous event studies have focused on individual investigation dates but lacked comparisons with other points in time and considerations of different dates in context with each other.

Third, with reference to the Volatility Hypotheses, the consideration of event-induced volatility also represents an aspect not previously investigated in the context of exogenous shocks. This dissertation also proves that the consideration of this aspect is relevant to the quality of the research results.

Fourth, the role of (company-specific) investor sentiment in moderating the impact of exogenous shocks on stock prices has not yet been investigated. In particular, the choice of three points in time during the COVID-19 outbreak for the investigation, also in this aspect, is another unique characteristic of the dissertation.

7.3 Limitations of the Dissertation and Further Studies

Despite the already mentioned implications for further research in Chapter 8.1, the study has further limitations that should be mentioned. The first limitation results from the method of calculating investor sentiment. As explained in the introduction and Chapter 4, the correct operationalization of investor sentiment is the subject of controversial debate and research. The decision favoring a specific approach always means a decision against numerous other approaches. A comparison of the OSI with the Daily News Sentiment Index, according to Wilson and Shapiro, also revealed that the trends develop differently, especially from the wider spread of COVID-19. A study by Kim *et al.* (2022) suggests that sentiment indicators using market indices have a higher predictive accuracy for stock returns than news sentiment. In addition, Buckman *et al.* (2020) show that the DNSI curve deviates from the curve of other sentiment indicators from 2020 onwards. A limitation of this study is the lack of investigation of the research questions with a different approach to measuring investor sentiment. Further research should shed more light on these differences and identify which types of sentiment indicators are suitable for use in specific contexts.

Research Question 6 looked at the emergence of CARs due to the various shocks, among other things. The overall conclusion was that investors' reactions to the shocks became ever more substantial, with the level of CARs increasing over time. This could be due to the events' increasing significance and perceived significance, which leads to a "dwindling optimism" among investors. The dwindling optimism is also reflected in increasingly negative investor sentiment regarding the course of the OSI. This correlation offers scope for future research approaches. They bring the question of whether increasing CARs occurs solely due to the events themselves, or possibly to the prevailing investor sentiment in the market, or whether there is actually a connection between the events, as the results of this dissertation suggest.

Two further aspects were not covered in the current study. These should be examined in more detail through further research. Firstly, more recent studies indicate that a sentiment-driven reaction by market participants is not always an irrational reaction, as initially assumed. However, in certain situations, sentiment-driven participants can act rationally as “contrarians” and display the opposite of the expected behavior. This behavior has not yet been further analyzed during exogenous shocks.

Furthermore, the current study's results suggest that positive investor sentiment “protects” stocks from more negative CARs. Further research should complement this finding with additional elements, such as the moderating effect of investor sentiment on the risk-reward relationship, especially during exogenous shocks. This will allow researchers to better understand investor sentiment's impact in the wake of exogenous shocks.

7.4 Final Conclusion

This study aimed to investigate the role of investor sentiment during exogenous shocks. As examples, three events in the context of the outbreak and spread of COVID-19 were selected as proxies for “shocks”. A new approach to aggregate investor sentiment for broad market indices showed that such an investor sentiment indicator has a Granger-causal relationship with the daily returns of the S&P 500 Index. The effects of the shocks on the returns of the stocks included in the index and their volatility development were also analyzed. Corresponding effects were documented and interpreted in context. Finally, the role of investor sentiment in the development of CARs was examined in more detail, and relevant new findings were also found here.

This dissertation thus makes a significant contribution to two aspects. On the one hand, it provides information on the effect of investor sentiment and thus contributes to the emerging and growing literature on behavioral finance. By focusing on the spread of COVID-19 in 2019 and 2020, the dissertation also contributes to a better understanding of the reaction of equity markets to exogenous shocks in general, but in particular to the further investigation of the interrelationships of the COVID-19 pandemic in particular.

In addition, the results of the study not only contribute to a better understanding of investor sentiment but also provide important implications for investors' portfolio design in the context of risk management. For example, to hedge their portfolios against exogenous shocks, investors could include shares that previously exhibited a correspondingly high level of investor sentiment. Furthermore, based on the available results, there are indications that events related to one another may “build up” and lead to "dwindling optimism" over time. However, further research must first provide additional findings and evidence.

REFERENCES

Abdi, H., & Molin, P. (2007). Lilliefors/Van Soest's Test of Normality. *Encyclopedia of Measurement and Statistics*, *1,* 540-544.

Abdmoulah, W. (2010). Testing the Evolving Efficiency of Arab Stock Markets. *International Review of Financial Analysis*, *19*(1), 25-34.

Aboody, D., Even-Tov, O., Lehavy, R., & Trueman, B. (2018). Overnight Returns and Firm-Specific Investor Sentiment. *Journal of Financial and Quantitative Analysis*, *53*(2), 485-505.

Aggarwal, D. (2022). Defining and measuring market sentiments: a review of the literature. *Qualitative Research in Financial Markets*, *14*(2), 270–288. https://doi.org/10.1108/qrfm-03-2018-0033

Aggarwal, D., & Mohanty, P. (2018). Do Indian Stock Market Sentiments Impact Contemporaneous Returns? *South Asian Journal of Business Studies*, 7(3), 332-346.

Agiakloglou, C., & Newbold, P. (1992). Empirical Evidence on Dickey-Fuller-type Tests. *Journal of Time Series Analysis*, *13*(6), 471-483.

Ahmed, B. (2020). Understanding the Impact of Investor Sentiment on the Price Formation Process: A Review of the Conduct of American Stock Markets. *The Journal of Economic Asymmetries*, *22*, e00172.

Akerlof, G. A. (1970). 4. The Market for 'Lemons': Quality Uncertainty and the Market Mechanism. *Market Failure or Success*, *66*.

Alam, M. M., Wei, H., & Wahid, A. N. (2021). COVID-19 Outbreak and Sectoral Performance of the Australian Stock Market: An Event Study Analysis. *Australian Economic Papers*, *60*(3), 482-495.

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and Contagious Infectious Diseases: Impact of the COVID-19 Virus on Stock Market Returns. *Journal of Behavioral and Experimental Finance*, *27*, 100326.

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *The Review of Corporate Finance Studies*, *9*(3), 593-621.

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19) — An Epidemic or Pandemic for Financial Markets. *Journal of Behavioral and Experimental Finance*, *27*, 100341. https://doi.org/10.1016/j.jbef.2020.100341

Allen, D. E., McAleer, M., & Singh, A. K. (2019). Daily Market News Sentiment and Stock Prices. *Applied Economics*, *51*(30), 3212-3235.

Allison, P. D. (2011). Longitudinal Data Analysis Using SAS. *Statistical Horizons*.

Alrabadi, D. W. H. (2015). A New Proxy for Investor Sentiment: Evidence from an Emerging Market. *Afro-Asian Journal of Finance and Accounting*, *5*(4), 334-343.

Al-Rjoub, S. A. M., & Al-Azzam, H. Q. (2019). Time varying Volatility and Asymmetric News Effect during Financial Crises. Evidence from DJIA, S&P 500, NASDAQ and FTSE 100 Indices. *International Journal of Banking, Accounting and Finance*, *10*(2), 117–143. https://doi.org/10.1504/IJBAAF.2019.099425

Al-Rjoub, S. A., & Azzam, H. (2012). Financial Crises, Stock Returns and Volatility in an Emerging Stock Market: The Case of Jordan. *Journal of Economic Studies*, *39*(2), 178–211. https://doi.org/10.1108/01443581211222653

American Hospital Association. (2020). *U.S. declares Coronavirus a public Health Emergency; CDC Updates Guidance*. Retrieved from: https://www.aha.org/news/headline/2020-01-31-us-declares-coronavirus-public-health-emergency-cdc-updates-guidance

Amromin, G., & Sharpe, S. A. (2014). From the Horse's Mouth: Economic Conditions and Investor Expectations of Risk and Return. *Management Science*, *60*(4), 845-866.

Anastasiou, D., Ballis, A., & Drakos, K. (2022). Constructing a Positive Sentiment Index for COVID-19: Evidence from G20 Stock Markets. *International Review of Financial Analysis*, *81,* 102-111.

Anderson, S. (2021). *Standard Error of the Mean vs. Standard Deviation*. Retrieved from: https://www.investopedia.com/ask/answers/042415/what-difference-between-standard-error-means-and-standard-deviation.asp

Arif, S., & Lee, C. M. C. (2014). Aggregate Investment and Investor Sentiment. *Review of Financial Studies*, *27*(11), 3241–3279. https://doi.org/10.1093/rfs/hhu054

Arrow, K. J. (1963). Uncertainty and the Welfare Economics of Medical Care. *The American Economic Review, 53*(5), 941–973.

Arrow, K. J. (1996). The Economics of Information: An Exposition. *Empirica*, *23*(2), 119-128.

Asgharian, H., Christiansen, C., & Hou, A. J. (2023). The Effect of Uncertainty on Stock Market Volatility and Correlation. *Journal of Banking & Finance*, *154*, 106929.

Ashraf, B. N. (2020). Economic Impact of Government Interventions during the COVID-19 Pandemic: International Evidence from Financial Markets. *Journal of Behavioral and Experimental Finance*, *27*. https://doi.org/10.1016/j.jbef.2020.100371

Atkins, A. B., & Dyl, E. A. (1990). Price Reversals, Bid-Ask Spreads, and Market Efficiency. *Journal of Financial and Quantitative Analysis*, *25*(4), 535-547.

Austin, D. (1993). An Event-Study Approach to Measuring Innovative Output: The Case of Biotechnology. *American Economic Review*, *83*(2), 253–258. https://doi.org/10.2307/2117673

Badola, S., Sahu, A. K., & Adlakha, A. (2023). A Systematic Review on Behavioral Biases Affecting Individual Investment Decisions. *Qualitative Research in Financial Markets*, *16*(3), 448-476.

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and Stock Market Volatility: An Industry Level Analysis. *Finance Research Letters*, *37*, 101748. https://doi.org/10.1016/j.frl.2020.101748

Bai, L., Wei, Y., Wei, G., Li, X., & Zhang, S. (2020). Infectious Disease Pandemic and permanent Volatility of international Stock Markets: A long-term Perspective. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2020.101709

Baker, M., & Stein, J. C. (2004). Market Liquidity as a Sentiment Indicator. *Journal of Financial Markets*, *7*(3), 271-299.

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives*, *21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious Investor Sentiment. *Journal of Financial Economics*, *104*(2), 272-287.

Baker, S. R., Bloom, N., & Terry, S. J. (2024). Using Disasters to estimate the Impact of Uncertainty. *Review of Economic Studies*, *91*(2), 720-747.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., & Viratyosin, T. (2020). The unprecedented Stock Market Impact of COVID-19. *National Bureau of Economic Research,* w26945.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742-758.

Balaban, E., & Constantinou, C. T. (2006). Volatility Clustering and Event-induced Volatility: Evidence from UK Mergers and Acquisitions. *The European Journal of Finance*, 12(5), 449-453.

Balaban, E., Bayar, A., & Faff, R. W. (2006). Forecasting Stock Market Volatility: Further International Evidence. *The European Journal of Finance*, *12*(2), 171-188.

Ball, R., & Brown, P. R. (2014). Ball and Brown (1968): A Retrospective. *The Accounting Review*, *89*(1), 1-26.

Ball, R., Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*, 159–78.

Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2014). The Cross-Section of Speculator Skill: Evidence from Day Trading. *Journal of Financial Markets*, *18*, 1-24.

Barberis, N. (2013). Psychology and the Financial Crisis of 2007-2008. *Financial innovation: too much or too little*, 15-28.

Barberis, N. (2018). Psychology-based Models of Asset Prices and Trading Volume. In *Handbook of behavioral economics: applications and foundations 1*, 79-175. North-Holland.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A Model of Investor Sentiment. *Journal of Financial Economics*, *49*(3), 307-343.

Bartram, S. M., & Bodnar, G. M. (2009). No Place to hide: The global Crisis in Equity Markets in 2008/2009. *Journal of International Money and Finance, 28(8),* 1246-1292.

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH Models: a Survey. *Journal of Applied Econometrics*, *21*(1), 79-109.

BBC (2020). *Coronavirus 'most severe Health Emergency' WHO has faced*. Retrieved from: https://www.bbc.com/news/world-53557577

BBC News (2022). *North Korea: 'First' Covid Cases prompt strict national Lockdown.* Retrieved from: https://www.bbc.com/news/world-asia-61416760

Beaver, W. (1981). Market Efficiency. In *Accounting Review*. Retrieved from: https://www.jstor.org/stable/246460?casa_token=boYQTBaJnz0AAAAA:HGXEVRmFqope6mMnAVhTOs2D1zE0h4McLN65JBU4oyHqKht6xsJWRnb8L0btaz4tTKNeg2BiHQj0i5bzU4S3FMM-MHCDmBXzk4T8RWnoE90HQUGcIw0Y

Będowska-Sójka, B. (2016). Liquidity Dynamics around Jumps: The Evidence from the Warsaw Stock Exchange. *Emerging Markets Finance and Trade*, *52*(12), 2740-2755.

Beer, F., & Zouaoui, M. (2013). Measuring Stock Market Investor Sentiment. *Journal of Applied Business Research*, *29*(1), 51-68.

Benkraiem, R., & Louhichi, W. (2009). Market Reaction to Sporting Results. *Management Decision*, *47*(1), 100–109. Retrieved from: https://www.emerald.com/insight/content/doi/10.1108/00251740910929722/full/html

Bentham, J. (1789). An Introduction to the Principles of Morals and Legislation. London: T. Payne and Sons.

Bergman, N. K., & Roychowdhury, S. (2008). Investor Sentiment and Corporate Disclosure. *Journal of Accounting Research*, *46*(5), 1057–1083. https://doi.org/10.1111/j.1475-679X.2008.00305.x

Berkman, H., Jacobsen, B., & Lee, J. B. (2011). Time-varying Rare Disaster Risk and Stock Returns. *Journal of Financial Economics*, *101*(2), 313–332. https://doi.org/10.1016/j.jfineco.2011.02.019

Berkman, H., Koch, P. D., Tuttle, L., & Zhang, Y. J. (2012). Paying Attention: Overnight Returns and the hidden Cost of buying at the Open. *Journal of Financial and Quantitative Analysis*, *47*(4), 715-741.

Berkmen, S. P., Gelos, G., Rennhack, R., & Walsh, J. P. (2012). The global financial Crisis: Explaining cross-country Differences in the Output Impact. *Journal of International Money and Finance*, *31*(1), 42-59.

Bernardo, A. E., & Welch, I. (2004). Liquidity and Financial Market Runs. *The Quarterly Journal of Economics*, *119*(1), 135-158.

Białkowski, J., Gottschalk, K., & Wisniewski, T. P. (2008). Stock Market Volatility around National Elections. *Journal of Banking & Finance*, *32*(9), 1941-1953.

Binder, J. J. (1998). The Event Study Methodology since 1969. *Review of Quantitative Finance and Accounting*, *11*(2), 111–137. https://doi.org/10.1023/A:1008295500105

Birru, J., & Young, T. (2022). Sentiment and Uncertainty. *Journal of Financial Economics*, *146*(3), 1148-1169.

Bissoondoyal-Bheenick, E., Do, H., Hu, X., & Zhong, A. (2020). Learning from SARS: Return and Volatility Connectedness in COVID-19. *Finance Research Letters*, 101796. https://doi.org/10.1016/j.frl.2020.101796

Black, F. (1986). Noise. *The Journal of Finance*, *41*(3), 529–543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

Blajer-Gołębiewska, A. & Czerwonka, L. (2012). Corporate Governance and Propensity to Share Information: The Long-Run Effect. *Corporate Ownership & Control*, 399.

Blajer-Gołębiewska, A. (2021). Individual Corporate Reputation and Perception of Collective Corporate Reputation regarding Stock Market Investments. *Plos one*, *16*(9), e0257323.

Blajer-Gołębiewska, A., & Nowak, S. (2024). Do their Reputations precede them? Stock market Reaction to Changes in corporate Reputation in the Context of Sector and Market Maturity. *Journal of International Studies*, 17(1).

Blajer-Gołębiewska, A., Honecker, L., & Nowak, S. (2024). Investor Sentiment Response to COVID-19 Outbreak-Related News: A Sectoral Analysis of US Firms. *The North American Journal of Economics and Finance*, *71*, 102121.

Blendon, R. J., Benson, J. M., DesRoches, C. M., Raleigh, E., & Taylor-Clark, K. (2004). The Public's Response to Severe Acute Respiratory Syndrome in Toronto and the United States. *Clinical Infectious Diseases, 38(7),* 925–931. https://doi.org/10.1086/382355

Bloomfield, R., Libby, R., Nelson, M. W., Bloomfield, R., Libby, R., & Nelson, M. W. (1999). Confidence and the Welfare of Less-Informed Investors. *Accounting, Organizations and Society*, *24*(8), 623–647. Retrieved from: https://EconPapers.repec.org/RePEc:eee:aosoci:v:24:y:1999:i:8:p:623-647

Bollen, J., & Mao, H. (2011). Twitter Mood as a Stock Market Predictor. *Computer*, *44*(10), 91–94. https://doi.org/10.1109/MC.2011.323

Bollerslev, T. (1986). Generalized autoregressive conditional Heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Boone, L. (2020). *Coronavirus: Living with Uncertainty.* Retrieved from: https://oecdecoscope.blog/2020/09/16/coronavirus-living-with-uncertainty/

Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). COVID-19 Pandemic and Investor Herding in International Stock Markets. *Risks*, *9*(9), 168.

Bouteska, A. (2019). The Effect of Investor Sentiment on Market Reactions to Financial Earnings Restatements: Lessons from the United States. *Journal of Behavioral and Experimental Finance*, *24*, 100241.

Bowden, J., & Gemayel, R. (2022). Sentiment and Trading Decisions in an ambiguous Environment: a Study on Cryptocurrency Traders. *Journal of International Financial Markets, Institutions and Money, 80*, 101622.

Bowman, R. G. (1983). Understanding and conducting Event Studies. *Journal of Business Finance & Accounting*, *10*(4), 561-584.

Bpb. (2017). *Homo Oeconomicus | bpb*. Retrieved from: https://www.bpb.de/nachschlagen/lexika/lexikon-der-wirtschaft/19635/homo-oeconomicus

Bram, J., Orr, J., & Rapaport, C. (2002). Measuring the Effects of the September 11 Attack on New York City. *Federal Reserve Bank of New York Economic Policy Review*, *8*(2), 5–20. Retrieved from: http://www.ny.frb.org/research/epr/%5Cnhttp://search.ebscohost.com/login.aspx?direct=true&db=ecn&AN=0637233&site=ehost-live

Brandt, M. (2021). *Infografik: Das Virus, das die Welt umspannt.* Retrieved from: https://de.statista.com/infografik/20647/verbreitung-des-coronavirus-aus-wuhan/

Breckenfelder, J., & Tédongap, R. (2012). Asymmetry Matters: A High-Frequency Risk-Reward Trade-Off. *Available at SSRN 1828283*.

Bremer, M., & Sweeney, R. J. (1991). The Reversal of Large Stock-Price Decreases. *The Journal of Finance*, *46*(2), 747-754.

Brenner, M. (1979). The Sensitivity of the Efficient Market Hypothesis to Alternative Specifications of the Market Model. *The Journal of Finance*, *34*(4), 915–929. https://doi.org/10.1111/j.1540-6261.1979.tb03444.x

Breusch, T. S., & Pagan, A. R. (1979). A simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica: Journal of the Econometric Society*, 1287-1294.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). COVID-19, Lockdowns and Well-Being: Evidence from Google Trends. *Journal of Public Economics*, *193*, 104346.

Brown, G. W., & Cliff, M. T. (2004). Investor Sentiment and the near-term Stock Market. *Journal of Empirical Finance*, *11*(1), 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001

Brown, G. W., & Cliff, M. T. (2005). Investor Sentiment and Asset Valuation. *Journal of Business*, *78*(2), 405–440. https://doi.org/10.1086/427633

Brown, K. C., Harlow, W. V., & Tinic, S. M. (1988). Risk Aversion, Uncertain Information, and Market Efficiency. *Journal of Financial Economics*, *22*(2), 355-385.

Brown, S. J., & Warner, J. B. (1980). Measuring Security Price Performance. *Journal of Financial Economics*, *8*(3), 205-258.

Brown, S. J., & Warner, J. B. (1985). Using Daily Stock Returns: The Case of Event Studies. *Journal of Financial Economics*, *14*(1), 3-31.

Brzezicka, J., & Wisniewski, R. (2014). Homo Oeconomicus and Behavioral Economics. *Contemporary Economics*, *8*(4), 353–364. https://doi.org/10.5709/ce.1897-9254.150

Bu, Q. (2021). Are all the Sentiment Measures the same?. *Journal of Behavioral Finance*, *24*(2), 161-170.

Buckman, S. R., Shapiro, A. H., Sudhof, M., & Wilson, D. J. (2020). News Sentiment in the Time of COVID-19. *FRBSF Economic Letter*, *8(1),* 5-10.

Bundeszentrale für politische Bildung (2017). *vollkommener Markt | bpb*. Retrieved from: https://www.bpb.de/nachschlagen/lexika/lexikon-der-wirtschaft/21070/vollkommener-markt

Burch, T. R., Emery, D. R., & Fuerst, M. E. (2016). Who Moves Markets in a Sudden Marketwide Crisis? Evidence from 9/11. *Journal of Financial and Quantitative Analysis*, *51*(2), 463-487.

Burghardt, M., Czink, M., & Riordan, R. (2008). Retail Investor Sentiment and the Stock Market. *Available at SSRN 1100038*.

Cable, J., & Holland, K. (1999). Modelling normal Returns in Event Studies: a Model-Selection Approach and Pilot Study. *The European Journal of Finance*, *5*(4), 331-341.

Cable, J., & Holland, K. (1999). Regression vs. Non-Regression Models of Normal Returns: Implications for Event Studies. *Economics Letters*, *64*(1), 81–85. https://doi.org/10.1016/s0165-1765(99)00065-8

Cambridge University Press. (n.d.). *Perception*. *Cambridge dictionary*. Retrieved from: https://dictionary.cambridge.org/dictionary/english/perception

Campbell, C. J., Wesley, C. E., Campbell, C. J., & Wesley, C. E. (1993). Measuring Security Price Performance using daily NASDAQ Returns. *Journal of Financial Economics*, *33*(1), 73–92. Retrieved from: https://EconPapers.repec.org/RePEc:eee:jfinec:v:33:y:1993:i:1:p:73-92

Campbell, J. Y., & Kyle, A. S. (1993). Smart Money, Noise Trading and Stock Price Behaviour. *The Review of Economic Studies*, *60*(1), 1-34.

Canbaş, S., & Kandır, S. Y. (2009). Investor Sentiment and Stock Returns: Evidence from Turkey. *Emerging Markets Finance and Trade*, *45*(4), 36-52.

Cao, M., & Wei, J. (2005). Stock Market Returns: A Note on Temperature Anomaly. *Journal of Banking & Finance*, *29*(6), 1559-1573.

Capital.com (2024). *S&P 500 Definition*. Retrieved from: https://capital.com/s-p-500-definition

Carter, D. A., & Simkins, B. J. (2004). The Market's Reaction to unexpected, catastrophic Events: the Case of Airline Stock Returns and the September 11th Attacks. *The Quarterly Review of Economics and Finance*, *44*(4), 539-558.

Cevik, E., Kirci Altinkeski, B., Cevik, E. I., & Dibooglu, S. (2022). Investor Sentiments and Stock Markets during the COVID-19 Pandemic. *Financial Innovation*, *8*(1), 69.

Chang, Y. Y. C., Faff, R. W., & Hwang, C. Y. (2012). Local and global Sentiment Effects, and the Role of Legal, Information and Trading Environments. *Information and Trading Environments (February 28, 2012)*.

Charles, A., & Darné, O. (2006). Large Shocks and the September 11th Terrorist Attacks on International Stock Markets. *Economic Modelling*, *23*(4), 683-698. https://www.sciencedirect.com/science/article/pii/S026499930600040X

Chau, F., Deesomsak, R., & Koutmos, D. (2016). Does Investor Sentiment really matter?. *International Review of Financial Analysis, 48*, 221-232.

Chaudhary, R., Bakhshi, P., & Gupta, H. (2020). Volatility in international Stock Markets: An empirical Study during COVID-19. *Journal of Risk and Financial Management*, *13*(9), 208.

Chebbi, K., Ammer, M. A., & Hameed, A. (2021). The COVID-19 Pandemic and Stock Liquidity: Evidence from S&P 500. *The Quarterly Review of Economics and Finance*, *81*, 134-142.

Chen, A. H., & Siems, T. F. (2002). An empirical Analysis of the Capital Markets' Response to cataclysmic Events. *Dallas: Southern Methodist University, Cox School of Business, Working Paper*.

Chen, A. H., & Siems, T. F. (2007). The Effects of Terrorism on Global Capital Markets. *The Economic Analysis of Terrorism*, 99-122.

Chen, C. R., Mohan, N. J., & Steiner, T. L. (1999). Discount Rate Changes, Stock Market Returns, Volatility, and Trading Volume: Evidence from Intraday Data and Implications for Market Efficiency. *Journal of Banking & Finance*, *23*(6), 897-924.

Chen, C., Liu, L., & Zhao, N. (2021). Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The case of COVID-19. *Research on Pandemics*, 166-177. https://doi.org/10.1080/1540496X.2020.1787150

Chen, H., Chong, T. T. L., & Duan, X. (2010). A Principal-Component Approach to Measuring Investor Sentiment. *Quantitative Finance*, *10*(4), 339–347. https://doi.org/10.1080/14697680903193389

Chen, H., Chong, T. T. L., & She, Y. (2014). A Principal Component Approach to Measuring Investor Sentiment in China. *Quantitative Finance*, *14*(4), 573–579. https://doi.org/10.1080/14697688.2013.869698

Chen, M. H., Jang, S. C. (Shawn), & Kim, W. G. (2007). The Impact of the SARS Outbreak on Taiwanese Hotel Stock Performance: An Event-Study Approach. *International Journal of Hospitality Management*, *26*(1), 200–212. https://doi.org/10.1016/j.ijhm.2005.11.004

Cheng, P., Quek, C., & Mah, M. L. (2007). Predicting the Impact of Anticipatory Action on US Stock Market—An Event Study using ANFIS (a neural fuzzy Model). *Computational Intelligence, 23*(2)*,* 117-141.

Cheung, A. W. K., & Roca, E. (2013). The Effect on Price, Liquidity and Risk when Stocks are added to and deleted from a Sustainability Index: Evidence from the Asia Pacific Context. Journal of Asian Economics, 24, 51–65. https://doi.org/10.1016/j.asieco.2012.08.002

Chion, S. J., & Veliz, C. N. (2008). On the Normality of Stock Return Distributions: Latin American Markets, 2000-2007. *Journal of CENTRUM Cathedra, 1*(2*),* 90-108.

Chong, C. W., Ahmad, M. I., & Abdullah, M. Y. (1999). Performance of GARCH Models in Forecasting Stock Market Volatility. *Journal of Forecasting, 18*(5*)*, 333-343.

Chong, T. T. L., & Ng, W. K. (2008). Technical Analysis and the London Stock Exchange: Testing the MACD and RSI Rules using the FT30. *Applied Economics Letters*, *15*(14), 1111–1114. https://doi.org/10.1080/13504850600993598

Chou, R., Engle, R. F., & Kane, A. (1992). Measuring Risk Aversion from Excess Returns on a Stock Index. *Journal of Econometrics*, *52*(1-2), 201-224.

Chowdhury, E. K., Dhar, B. K., & Stasi, A. (2022). Volatility of the US Stock Market and Business Strategy during COVID-19. *Business Strategy & Development*, *5*(4), 350-360.

Chung, C. Y., & Wang, K. (2016). The Impact of individual Investor Trading on Information Asymmetry in the Korean Stock Market. *North American Journal of Economics and Finance*, *37*, 472–484. https://doi.org/10.1016/j.najef.2016.05.005

Chung, C. Y., Liu, C., & Wang, K. (2016). Institutional Investor Trading in a Short Investment Horizon: Evidence from the Korean Stock Market. *Emerging Markets Finance and Trade*, *52*(4), 1002–1012. https://doi.org/10.1080/1540496X.2015.1025648

Chung, S. L., Hung, C. H., & Yeh, C. Y. (2012). When does Investor Sentiment predict Stock Returns? *Journal of Empirical Finance*, *19*(2), 217-240.

Çıtak, L., Akel, V., & Ersoy, E. (2018). Investors' Reactions to the Announcement of New Constituents of BIST Sustainability Index. in: R. Mario & S. Testarmata (Eds.), *Value Sharing for Sustainable and Inclusive Development*, 270–289. IGI Global. https://doi.org/10.4018/978-1-5225-3147-0.ch012

Clougherty, J. A., & Duso, T. (2011). Using Rival Effects to identify Synergies and improve Merger Typologies. *Strategic Organization, 9(4),* 310-335.

Cohen, L., & Frazzini, A. (2008). Economic Links and Predictable Returns. *The Journal of Finance, 63(4),* 1977-2011.

Cohn, M. (2021). *GameStop and the Rise of Retail Investing: How a group of Reddit Users took Wall Street by Storm*. The New York Times. Retrieved from: https://www.nytimes.com/2021/01/27/business/gamestop-wall-street-bets.html

Colón-De-Armas, C., Rodriguez, J., & Romero, H. (2017). Investor Sentiment and US Presidential Elections. *Review of Behavioral Finance*, *9*(3), 227-241.

Congressional Research Service. (2021). *Unemployment Rates during the COVID-19 Pandemic (R46554).* Retrieved from: https://crsreports.congress.gov/product/pdf/R/R46554/9

Copeland, T. E., Weston, J. F., & Shastri, K. (2005). *Financial Theory and Corporate Policy* (Vol. 4). Boston: Pearson Addison Wesley.

Corbet, S., Gurdgiev, C., & Meegan, A. (2018a). Long-Term Stock Market Volatility and the Influence of Terrorist Attacks in Europe. *Quarterly Review of Economics and Finance*, *68*, 118–131. https://doi.org/10.1016/j.qref.2017.11.012

Corrado, C. J. (1989). A Nonparametric Test for Abnormal Security-Price Performance in Event Studies. *Journal of Financial Economics*, *23*(2), 385–395. https://doi.org/10.1016/0304-405X(89)90064-0

Corrado, C.J. (2011). Event Studies: A Methodology Review. *Accounting & Finance, 51*(1), 207–234. doi:10.1111/j.1467-629x.2010.00375.x

Corredor, P., Ferrer, E., & Santamaria, R. (2013). Investor Sentiment Effect in Stock Markets: Stock Characteristics or Country-Specific Factors? *International Review of Economics & Finance*, *27*, 572-591.

Court, L. M. (1941). Entrepreneurial and Consumer Demand Theories for Commodity Spectra: Part I. *Econometrica: Journal of the Econometric Society*, 135-162. https://doi.org/10.2307/1906875

Cowan, A. R. (1992). Nonparametric Event Study Tests. *Review of Quantitative Finance and Accounting, 2,* 343-358.

Cowan, A. R., Nayar, N., & Singh, A. K. (1990). Stock Returns before and after Calls of Convertible Bonds. *Journal of Financial and Quantitative Analysis, 25(4)*, 549-554.

Cox, D. R., & Peterson, D. R. (1994). Stock Returns following large One-Day Declines: Evidence on short-term Reversals and longer-term Performance. *The Journal of Finance*, *49*(1), 255-267.

Curran, M. M., & Moran, D. (2007). Impact of the FTSE4Good Index on Firm Price: An Event Study. Journal of Environmental Management, 82(4), 529-537.

Curto, J. D., & Serrasqueiro, P. (2022). The Impact of COVID-19 on S&P 500 Sector Indices and FATANG Stocks Volatility: An expanded APARCH Model. *Finance Research Letters*, *46*, 102247.

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of all FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies*, *28*(1), 1–32. https://doi.org/10.1093/rfs/hhu072

Das, K. R., & Imon, A. H. M. R. (2016). A brief Review of Tests for Normality. *American Journal of Theoretical and Applied Statistics, 5(1),* 5-12.

Das, S., & King, A. Z. (2021). Measuring the Informativeness of Earnings Announcements: The Role of Event Windows. *The Quarterly Review of Economics and Finance, 82*, 350-367.

Dash, S. R., & Maitra, D. (2022). The COVID-19 Pandemic Uncertainty, Investor Sentiment, and Global Equity Markets: Evidence from the Time-Frequency Co-Movements. *The North American Journal of Economics and Finance*, *62*, 101712.

Daxhammer, R. J., & Facsar, M. (2017). *Behavioral Finance: Verhaltenswissenschaftliche Finanzmarktforschung im Lichte begrenzt rationaler Marktteilnehmer*. UVK Verlag.

De Bondt, W. F., & Thaler, R. (1985). Does the Stock Market overreact?. *The Journal of Finance*, *40*(3), 793-805.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990a). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*(4), 703–738. https://doi.org/10.1086/261703

Del Giudice, A., & Paltrinieri, A. (2017). The Impact of the Arab Spring and the Ebola Outbreak on African Equity Mutual Fund Investor Decisions. *Research in International Business and Finance*, *41*, 600-612.

Delcey, T. (2018). Efficient Market Hypothesis, Eugene Fama and Paul Samuelson: A Reevaluation. Economia *9(1),* 37-58.

deLisle, J. (2003). SARS, Greater China, and the Pathologies of Globalization and Transition. *Orbis*, *47*(4), 587–604. https://doi.org/10.1016/S0030-4387(03)00076-0

Deutsches Aktieninstitut e.V. (2021). *Aktionärszahlen 2020: Deutsche begeistern sich mehr und mehr für Aktien*. Retrieved from: https://www.dai.de/detail/aktionaerszahlen-2020-deutsche-begeistern-sich-mehr-und-mehr-fuer-aktien

DeVault, L., Sias, R., & Starks, L. (2019). Sentiment Metrics and Investor Demand. *The Journal of Finance*, *74*(2), 985-1024.

Dhall, R., & Singh, B. (2020). The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market. *Millennial Asia*, *11*(3), 366-390.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association, 74(366),* 427-431.

Dictionary, C. E. (2018). *PERCEPTION | Bedeutung im Cambridge Englisch Wörterbuch*. Retrieved from: https://dictionary.cambridge.org/de/worterbuch/englisch/perception

Ding, M., Chen, Y., & Bressler, S. L. (2006). Granger Causality: Basic Theory and Application to Neuroscience. *Handbook of Time Series Analysis: Recent Theoretical Developments and Applications*, 437-460.

Ding, W., Mazouz, K., & Wang, Q. (2021). Volatility Timing, Sentiment, and the Short-Term Profitability of VIX-based Cross-Sectional Trading Strategies. *Journal of Empirical Finance*, *63*, 42-56.

Doh, J. P., Howton, S. D., Howton, S. W., & Siegel, D. S. (2010). Does the Market respond to an Endorsement of Social Responsibility? The Role of Institutions, Information, and Legitimacy. *Journal of Management, 36*(6), 1461-1485.

Dolley, J. (1933). Characteristics and Procedure of Common Stock Split-Ups. *Harvard Business Review*, 316–326. Retrieved from: https://scholar.google.com/scholar?hl=de&as_sdt=0%2C5&q=Characteristics+and+procedure+of+common+stock+split-ups&btnG=

Donadelli, M., Kizys, R., & Riedel, M. (2017). Dangerous Infectious Diseases: Bad News for Main Street, Good News for Wall Street?. *Journal of Financial Markets*, *35*, 84-103.

Doornik, J. A., & Hansen, H. (2008). An Omnibus Test for univariate and multivariate Normality. *Oxford Bulletin of Economics and Statistics, 70,* 927-939.

Dowd, J. B., Andriano, L., Brazel, D. M., Rotondi, V., Block, P., Ding, X., Liu, Y & Mills, M. C. (2020). Demographic Science Aids in Understanding the Spread and Fatality Rates of COVID-19. *Proceedings of the National Academy of Sciences*, *117*(18), 9696-9698.

Duan, C., Grover, V., & Balakrishnan, N. (2009). Business Process Outsourcing: an Event Study on the Nature of Processes and Firm Valuation. *European Journal of Information Systems*, *18*(5), 442-457.

Duz Tan, S., & Tas, O. (2021). Social Media Sentiment in International Stock Returns and Trading Activity. *Journal of Behavioral Finance*, *22*(2), 221-234. https://doi.org/10.1080/15427560.2020.1772261

Dyckman, T., Philbrick, D., & Stephan, J. (1984). A Comparison of Event Study Methodologies using Daily Stock Returns: A Simulation Approach. *Journal of Accounting Research*, 1-30.

Dzielinski, M. (2012). Measuring Economic Uncertainty and its Impact on the Stock Market. *Finance Research Letters*, *9*(3), 167–175. https://doi.org/10.1016/j.frl.2011.10.003

Eden, L., Miller, S. R., Khan, S., Weiner, R. J., & Li, D. (2022). The Event Study in International Business Research: Opportunities, Challenges, and Practical Solutions. *Journal of International Business Studies*, *53*(5), 803.

Edey, M. (2009). The Global Financial Crisis and its Effects. *Economic Papers: A Journal of Applied Economics and Policy, 28*(3), 186-195.

El Ghoul, S., Guedhami, O., Mansi, S. A., & Sy, O. (2023). Event Studies in International Finance Research. *Journal of International Business Studies*, *54*(2), 344.

Engelhardt, N., Krause, M., Neukirchen, D., & Posch, P. N. (2021). Trust and Stock Market Volatility during the COVID-19 Crisis. *Finance Research Letters*, *38*, 101873. https://doi.org/10.1016/j.frl.2020.101873

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Ewing, B. T., Hein, S. E., & Kruse, J. B. (2006). Insurer Stock Price Responses to Hurricane Floyd: An Event Study Analysis using Storm Characteristics. *Weather and Forecasting*, *21*(3), 395-407. https://doi.org/10.2139/ssrn.502866

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance, 46*(5)*,* 1575-1617.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance, 47*(2)*,* 427-465.

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, *116*(1), 1-22.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. In *International Economic Review*, *10*(1), 1-21. https://www.jstor.org/stable/2525569

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global Economic Uncertainty matter for the Volatility and Hedging Effectiveness of Bitcoin? *International Review of Financial Analysis*, *61*, 29–36. https://doi.org/10.1016/j.irfa.2018.12.010

Federal Reserve Bank of San Francisco. *Daily News Sentiment Index.* Retrieved from: https://www.frbsf.org/research-and-insights/data-and-indicators/daily-news-sentiment-index/

Feria-Domínguez, J. M., Paneque, P., & Gil-Hurtado, M. (2017). Risk Perceptions on Hurricanes: Evidence from the US Stock Market. *International Journal of Environmental Research and Public Health*, *14*(6), 600.

Fisher, K. L., & Statman, M. (2000). Investor Sentiment and Stock Returns. *Financial Analysts Journal*, *56*(2), 16–23. https://doi.org/10.2469/faj.v56.n2.2340

Flammer, C. (2013). Corporate Social Responsibility and Shareholder Reaction: The Environmental Awareness of Investors. *Academy of Management Journal*, *56*(3), 758-781.

Foster, G. (1980). Accounting Policy Decisions and Capital Market Research. *Journal of Accounting and Economics*, *2*(1), 29-62.

Franses, P. H., & Van Dijk, D. (1996). Forecasting Stock Market Volatility using (non-linear) GARCH Models. *Journal of Forecasting, 15(3),* 229-235.

Freeman, D. A. (2006). *On the so-called "Huber-Sandwich Estimator" and "Robust Standard Errors."* Retrieved from: https://www.stat.berkeley.edu/~census/mlesan.pdf

French, J. (2018a). Market Moods: an Investor Sentiment Event Study. *Foresight*, *20*(5), 488–506. https://doi.org/10.1108/FS-02-2018-0018

Frydman, R., Mangee, N., & Stillwagon, J. (2021). How Market Sentiment Drives Forecasts of Stock Returns. *Journal of Behavioral Finance*, *22*(4), 351-367.

Gabler. (2020). *Markt • Definition | Gabler Wirtschaftslexikon*. Retrieved from: https://wirtschaftslexikon.gabler.de/definition/markt-40513

Gallant, C. (2017). *Is it Possible to Measure Investor Sentiment?* Retrieved from: https://www.investopedia.com/ask/answers/06/investorsentiment.asp

Gao, B., & Liu, X. (2020). Intraday Sentiment and Market Returns. *International Review of Economics and Finance*, *69*, 48–62. https://doi.org/10.1016/j.iref.2020.03.010

Gao, B., & Yang, C. (2017). Forecasting Stock Index Futures Returns with Mixed-Frequency Sentiment. *International Review of Economics and Finance*, *49*, 69–83. https://doi.org/10.1016/j.iref.2017.01.020

Gao, L., & Süss, S. (2015). Market Sentiment in Commodity Futures Returns. *Journal of Empirical Finance*, *33*, 84-103.

Gao, Z., Ren, H., & Zhang, B. (2020). Googling Investor Sentiment around the World. *Journal of Financial and Quantitative Analysis*, *55*(2), 549-580.

García, D. (2013). Sentiment during Recessions. *The Journal of Finance*, *68*(3), 1267-1300.

Garson, G. D. (2012). Testing Statistical Assumptions. *NC Statistical Associates Publishing*.

Gerpott, T. J. (2009). Ereignisstudie. In *Empirische Mastertechniken,* 203-234. Gabler Verlag. https://doi.org/10.1007/978-3-8349-8278-0_7

Gilbert, G. (2018). Hurricane Matthew: Measuring the Stock Market Reaction on the Insurance Industry.

Glaser, M., Nöth, M., & Weber, M. (2003). Behavioral Finance. *Rationalitätskonzepte, Entscheidungsverhalten und ökonomische Modellierung*, *3*.

Glaser, M., Schmitz, P., & Weber, M. (2009). Individual Investor Sentiment and Stock Returns-What Do We Learn from Warrant Traders?. *Available at SSRN 923526*.

Goel, S., & Shawky, H. A. (2009). Estimating the Market Impact of Security Breach Announcements on Firm Values. *Information & Management*, *46*(7), 404-410.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced Mood, Institutional Investors, and Stock Returns. *The Review of Financial Studies*, *28*(1), 73-111.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate Governance and Equity Prices. *The Quarterly Journal of Economics, 118(1),* 107-156.

Goodell, J. W., & Huynh, T. L. D. (2020). Did Congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters, 36,* 101578.

Goodell, J. W., Kumar, S., Rao, P., & Verma, S. (2023). Emotions and Stock Market Anomalies: A Systematic Review. *Journal of Behavioral and Experimental Finance, 37,* 100722.

Google Trends. (2024). *Interest in "Corona" in the U.S. from December 2019 to April 2020*. Google. Retrieved September 22, 2024, from https://trends.google.de/trends/explore?date=2019-12-01%202020-04-30&geo=US&q=corona&hl=de

Gosepath, S. (2002). Eine einheitliche Konzeption von Rationalität: Ein Zugang aus Sicht der Analytischen Philosophie. *Zugänge zur Rationalität der Zukunft*, 29-52.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*. 37 (3): 424–438. doi:10.2307/1912791

Greenacre, M., Groenen, P. J., Hastie, T., d'Enza, A. I., Markos, A., & Tuzhilina, E. (2022). Principal Component Analysis. *Nature Reviews Methods Primers, 2(1),* 100.

Greenwood, R., & Shleifer, A. (2014). Expectations of Returns and Expected Returns. *The Review of Financial Studies, 27*(3), 714-746.

Guo, H., & Whitelaw, R. F. (2006). Uncovering the Risk–Return Relation in the Stock Market. *The Journal of Finance*, *61*(3), 1433-1463.

Guo, H., Kassa, H., & Ferguson, M. F. (2014). On the Relation between EGARCH Idiosyncratic Volatility and Expected Stock Returns. *Journal of Financial and Quantitative Analysis, 49(1),* 271-296.

Guo, L., & Mech, T. S. (2000). Conditional Event Studies, Anticipation, and Asymmetric Information: the Case of seasoned Equity Issues and Pre-Issue Information Releases. *Journal of Empirical Finance, 7(*2), 113-141.

Hafez, P., & Xie, J. (2016). News Beta: Factoring Sentiment Risk into Quant Models. *The Journal of Investing*, *25*(3), 88–104. https://doi.org/10.3905/joi.2016.25.3.088

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media Coverage and Financial Markets Behavior—A Sectoral Inquiry. *Journal of Behavioral and Experimental Finance*, *27*. https://doi.org/10.1016/j.jbef.2020.100343

Harvey, A. C., & Stock, J. H. (1989). Estimating Integrated Higher-Order Continuous Time Autoregressions with an Application to Money-Income Causality. *Journal of Econometrics*, *42*(3), 319-336.

Hauser, S. E., & Hauser, S. E. (2003a). Grundlagen zur Informationseffizienz und Informationsverarbeitung an Kapitalmärkten. In *Informationsverarbeitung am Neuen Markt*, 19-83. Deutscher Universitätsverlag. https://doi.org/10.1007/978-3-322-81603-0_2

Hauser, S. E., & Hauser, S. E. (2003b). Untersuchungsmethodik. In *Informationsverarbeitung am Neuen Markt*, 131-180. Deutscher Universitätsverlag. https://doi.org/10.1007/978-3-322-81603-0_4

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's Impact on Stock Prices Across Different Sectors—An Event Study Based on the Chinese Stock Market. *Emerging Markets Finance and Trade*, *56*(10), 2198–2212. https://doi.org/10.1080/1540496X.2020.1785865

He, Z. (2022). Asymmetric Impacts of individual Investor Sentiment on the time-varying Risk-Return Relation in Stock Market. *International Review of Economics & Finance*, *78*, 177-194.

He, Z., He, L., & Wen, F. (2019). Risk Compensation and Market Returns: The Role of Investor Sentiment in the Stock Market. *Emerging Markets Finance and Trade*, *55*(3), 704-718.

Held, A. (2004). *Die Informationseffizienz des deutschen Kapitalmarktes. Messkonzepte und Forschungsergebnisse*. GRIN Verlag.

Hicks, J. R. (1936). Keynes' Theory of Employment, Interest and Money. *The Economic Journal*, *46*(182), 238-253.

Hirshleifer, D., & Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. In *Journal of Finance*, *58(3),* 1009–1032. https://doi.org/10.1111/1540-6261.00556

Hon, T. Y., Moslehpour, M., & Woo, K. Y. (2021). Review on Behavioral Finance with Empirical Evidence. *Advances in Decision Sciences*, *25*(4), 1-30.

Horn, G. A. (2022). *Schock, Definition | Gabler Wirtschaftslexikon*. Retrieved December 28, 2020, from https://wirtschaftslexikon.gabler.de/definition/schock-42921

Hribar, P., & McInnis, J. (2012). Investor Sentiment and Analysts' Earnings Forecast Errors. *Management Science*, *58*(2), 293–307. https://doi.org/10.1287/mnsc.1110.1356

Hsieh, S. F., Chan, C. Y., & Wang, M. C. (2020). Retail Investor Attention and Herding Behavior. *Journal of Empirical Finance*, *59*, 109-132.

Huber, C., Finelli, L., & Stevens, W. (2018). The Economic and Social Burden of the 2014 Ebola Outbreak in West Africa. *The Journal of Infectious Diseases*, *218* (5), 698–704. https://doi.org/10.1093/infdis/jiy213

Huo, X., & Qiu, Z. (2020). How does China's Stock Market react to the Announcement of the COVID-19 Pandemic Lockdown? *Economic and Political Studies*, 1–26. https://doi.org/10.1080/20954816.2020.1780695

Ichev, R., & Marinč, M. (2018). Stock Prices and Geographic Proximity of Information: Evidence from the Ebola Outbreak. *International Review of Financial Analysis*, *56*, 153-166.

Jaziri, M., & Abdelhedi, M. (2018). Islamic Occasions and Investor Sentiment. *International Journal of Islamic and Middle Eastern Finance and Management*, *11*(2), 194–212. https://doi.org/10.1108/IMEFM-08-2017-0225

Jegadeesh, N., & Titman, S. (1993). Returns to buying Winners and selling Losers: Implications for Stock Market Efficiency. *Journal of Finance, 48(1)*, 65-91.

Jiang, Y. (2011, August). Investor Sentiment and Stock Market Response to Earnings Announcement. In *2011 International Conference on Management and Service Science*, 1-4. IEEE.

John, K., & Li, J. (2021). COVID-19, Volatility Dynamics, and Sentiment Trading. *Journal of Banking & Finance*, *133*, 106162.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting Abnormal Stock Returns and Trading Volume using Investor Sentiment: Evidence from Online Search. *International Journal of Forecasting*, *27*(4), 1116-1127.

JPMorgan Chase. (n.d.). *The Changing Demographics of Retail Investors*. JPMorgan Chase Institute. Retrieved from: https://www.jpmorganchase.com/institute/all-topics/financial-health-wealth-creation/the-changing-demographics-of-retail-investors

Just, M., & Echaust, K. (2020). Stock Market Returns, Volatility, Correlation and Liquidity during the COVID-19 Crisis: Evidence from the Markov Switching Approach. *Finance Research Letters*, *37*, 101775.

Kahneman, D., & Thaler, R. H. (2006). Anomalies: Utility Maximization and Experienced Utility. *Journal of Economic Perspectives*, *20*(1), 221-234.

Kahneman, D., & Tversky, A. (2013). Prospect Theory: An Analysis of Decision under Risk. In *Handbook of the fundamentals of financial decision making: Part I*, 99-127.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock Market Cycle. In *American Economic Review, 93 (1),* 324–343. https://doi.org/10.1257/000282803321455322

Kandampully, J., & Duddy, R. (1999). Competitive Advantage through Anticipation, Innovation and Relationships. *Management Decision*, *37*(1), 51–56. https://doi.org/10.1108/00251749910252021

Kaplanski, G., & Levy, H. (2010). Exploitable Predictable Irrationality: The FIFA World Cup Effect on the U.S. Stock Market. *Journal of Financial and Quantitative Analysis*, *45*(2), 535–553. https://doi.org/10.1017/S0022109010000153

Karabulut, Y. (2013, October). Can Facebook predict Stock Market Activity?. In *AFA 2013 San Diego meetings paper*.

Kargol-Wasiluk, A., Wildowicz-Giegiel, A., & Zalesko, M. (2018). The Evolution of the Economic Man. From Homo Oeconomicus to Homo Moralis. *Gospodarka Narodowa. The Polish Journal of Economics*, *293*(1), 33–57. https://doi.org/10.33119/GN/100566

Keogh-Brown, M. R., & Smith, R. D. (2008). The Economic Impact of SARS: How does the Reality match the Predictions? *Health Policy*, *88*(1), 110–120. https://doi.org/10.1016/j.healthpol.2008.03.003

Khalfaoui, R., Nammouri, H., Labidi, O., & Jabeur, S. B. (2021). Is the COVID-19 Vaccine effective on the US Financial Market?. *Public Health, 198,* 177-179.

Khan, M., & Huq, U. (2012). Distribution of Risk and Return: A Statistical Test of Normality on Dhaka Stock Exchange. *Research Journal of Finance and Accounting, 3(3).*

Khatatbeh, I., Bani Hani, M., & Abu Alfoul, M. N. (2020). The Impact of COVID-19 Pandemic on Global Stock Markets: An Event Study. *International Journal of Economics and Business Administration*, *8*(4), 505-514.

Kim, J. H., & Shamsuddin, A. (2008). Are Asian Stock Markets efficient? Evidence from new multiple Variance Ratio Tests. *Journal of Empirical Finance*, *15*(3), 518-532.

Kim, K., Ryu, D., & Yang, H. (2021). Information Uncertainty, Investor Sentiment, and Analyst Reports. *International Review of Financial Analysis, 77,* 101835.

Kim, K., Ryu, D., & Yu, J. (2022). Is a sentiment-based Trading Strategy profitable?. *Investment Analysts Journal*, *51*(2), 94-107.

Kim, S. H., & Kim, D. (2014). Investor Sentiment from Internet Message Postings and the Predictability of Stock Returns. *Journal of Economic Behavior and Organization*, *107*, 708–729. https://doi.org/10.1016/j.jebo.2014.04.015

Kim, T., & Ha, A. (2010, August). Investor Sentiment and Market Anomalies. In *23rd Australasian Finance and Banking Conference*.

Kirchgässner, G. (2008). Homo Oeconomicus: The economic Model of Behaviour and its Applications in Economics and other Social Sciences (Vol. 6). Springer Science & Business Media.

Klein, A. (2023). *'Dumb Money' and the Lessons of the GameStop Saga*. The New York Times. Retrieved from: https://www.nytimes.com/2023/10/01/opinion/dumb-money-movie-gamestop-stock.html

Klein, A., & Rosenfeld, J. (1987). The Influence of Market Conditions on Event-Study Residuals. *Journal of Financial and Quantitative Analysis*, *22*(3), 345-351.

Klofstad, C. A. (2005). Interviews. *Encyclopedia of Social Measurement*, 359–363. https://doi.org/10.1016/B0-12-369398-5/00033-5

Koçak, E., Bulut, U., & Menegaki, A. N. (2022). The Resilience of green Firms in the Twirl of COVID-19: Evidence from S&P500 Carbon Efficiency Index with a Fourier Approach. *Business Strategy and the Environment*, *31*(1), 32-45.

Koenker, R. (1981). *A Note on Studentizing a Test for Heteroscedasticity*. Retrieved from: https://econpapers.repec.org/article/eeeeconom/v_3a17_3ay_3a1981_3ai_3a1_3ap_3a107-112.htm

Kolari, J. W., & Pynnönen, S. (2010). Event Study Testing with cross-sectional Correlation of abnormal Returns. *The Review of Financial Studies, 23(11),* 3996-4025.

Kothari, S., & Warner, J. (2008). Econometrics of Event Studies,[w:] Handbook of Corporate Finance. Empirical Corporate Finance, Vol. 1, red. BE Eckbo.

Kotkatvuori-Örnberg, J., Nikkinen, J., & Äijö, J. (2013). Stock Market Correlations during the financial Crisis of 2008–2009: Evidence from 50 Equity Markets. *International Review of Financial Analysis*, *28*, 70-78.

KPMG. (2020). *Rebooting manufacturing in mainland China*. KPMG China. Retrieved from: https://assets.kpmg.com/content/dam/kpmg/cn/pdf/en/2020/02/rebooting-manufacturing-in-mainland-china.pdf

Krivin, D., Patton, R., Rose, E., & Tabak, D. (2003). Determination of the appropriate Event Window Length in individual Stock Event Studies. *Available at SSRN 466161*.

Kumar, A., & Lee, C. M. (2006). Retail Investor Sentiment and Return Comovements. *The Journal of Finance*, *61*(5), 2451-2486.

Kumari, J., & Mahakud, J. (2015). Does Investor Sentiment predict the Asset Volatility? Evidence from emerging Stock Market India. *Journal of Behavioral and Experimental Finance*, *8*, 25-39.

Lanfear, M. G., Lioui, A., & Siebert, M. (2017). Are Value Stocks More Exposed to Disaster Risk? Evidence from Extreme Weather Events. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2892948

Lanfear, M. G., Lioui, A., & Siebert, M. G. (2019). Market Anomalies and Disaster Risk: Evidence from extreme Weather Events. *Journal of Financial Markets*, *46*, 100477. https://doi.org/10.1016/j.finmar.2018.10.003

Lanfear, M., Lioui, A., & Siebert, M. (n.d.). Flight to Gold: Extreme Weather Events and Stock Returns Working Paper Series. In *papers.ssrn.com*. Retrieved December 31, 2020, from https://ssrn.com/abstract=2894147

Lee, B. Y., Alfaro-Murillo, J. A., Parpia, A. S., Asti, L., Wedlock, P. T., Hotez, P. J., & Galvani, A. P. (2017). The potential Economic Burden of Zika in the Continental United States. *PLOS Neglected Tropical Diseases*, *11*(4), e0005531. https://doi.org/10.1371/journal.pntd.0005531

Lee, C. C., & Chen, M. P. (2020). Do Natural Disasters and geopolitical Risks matter for Cross-Border Country exchange-traded Fund Returns?. *The North American Journal of Economics and Finance*, *51*, 101054.

Lee, C. M. C., Shleifer, A., & Thaler, R. H. (1991). Investor Sentiment and the Closed-End Fund Puzzle. *The Journal of Finance*, *46*(1), 75–109. https://doi.org/10.1111/j.1540-6261.1991.tb03746.x

Lee, G., & Ryu, D. (2024). Investor Sentiment or Information Content? A simple Test for Investor Sentiment Proxies. *The North American Journal of Economics and Finance,* 102222.

Lee, H. S. (2020). Exploring the initial Impact of COVID-19 Sentiment on US Stock Market using Big Data. *Sustainability*, *12*(16), 6648.

Lee, J. W., & McKibbin, W. J. (2004). Estimating the global economic Costs of SARS. In *Learning from SARS: preparing for the next Disease Outbreak: Workshop Summary*, 92-109. Washington, DC: National Academies Press.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock Market Volatility, Excess Returns, and the Role of Investor Sentiment. *Journal of Banking & Finance*, *26*(12), 2277-2299.

Lemmon, M. L., & Ni, S. X. (2008). The Effects of Investor Sentiment on Speculative Trading and Prices of Stock and Index Options. *Available at SSRN 1306237*.

Lemmon, M., & Portniaguina, E. (2006). Consumer Confidence and Asset Prices: Some Empirical Evidence. In *Review of Financial Studies*, 19(4), 1499–1529. https://doi.org/10.1093/rfs/hhj038

Li, T., Chen, H., Liu, W., Yu, G., & Yu, Y. (2023). Understanding the Role of Social Media Sentiment in Identifying Irrational Herding Behavior in the Stock Market. *International Review of Economics & Finance*, *87*, 163-179.

Liang, C., Tang, L., Li, Y., & Wei, Y. (2020). Which Sentiment Index is more informative to forecast Stock Market Volatility? Evidence from China. *International Review of Financial Analysis*, *71*, 101552.

Lilliefors, H. W. (1967). On the Kolmogorov-Smirnov Test for Normality with Mean and Variance Unknown. *Journal of the American Statistical Association, 62(318),* 399-402.

Lintner, J. (1965). Security Prices, Risk, and Maximum Gains from Diversification. *The Journal of Finance*, *20*(4), 587-615.

Liu, H., Ferreira, S., & Karali, B. (2021). Hurricanes as News? Assessing the Impact of Hurricanes on the Stock Market Returns of Energy Companies. *International Journal of Disaster Risk Reduction*, *66*, 102572.

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of environmental Research and public Health*, *17*(8), 2800.

Liu, Q., Huang, M., Zhao, L., & Lee, W. S. (2023). The dispositional Effects of Holidays on Investor Sentiment: Therapeutic and Hygienic. *Journal of Innovation & Knowledge*, *8*(2), 100358.

Liu, Q., Wang, X., & Du, Y. (2022). The weekly Cycle of Investor Sentiment and the Holiday Effect--An empirical Study of Chinese Stock Market based on Natural Language Processing. *Heliyon*, *8*(12).

Liu, S. (2015). Investor Sentiment and Stock Market Liquidity. *Journal of Behavioral Finance*, *16*(1), 51–67. https://doi.org/10.1080/15427560.2015.1000334

Liu, Y. H., Dai, S. R., Chang, F. M., Lin, Y. B., & Lee, N. R. (2020). Does the Investor Sentiment affect the Stock Returns in Taiwan's Stock Market under different Market States?. *Journal of Applied Finance and Banking*, *10*(5), 41-59.

Livnat, J., & Petrovits, C. (2011). Investor Sentiment, Post-Earnings Announcement Drift, and Accruals. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1262757

Llusa, F., & Tavares, J. (2007). The Economics of Terrorism: A Synopsis. *The Economics of Peace and Security Journal*, *2*(1).

Long, Z., & Zhao, Y. (2022). The Risk Spillover Effect of COVID-19 Breaking News on the Stock Market. *Emerging Markets Finance and Trade, 58(15),* 4321-4337.

Lúcio, F., & Caiado, J. (2022). COVID-19 and Stock Market Volatility: A Clustering Approach for S&P 500 Industry Indices. *Finance Research Letters*, *49*, 103141.

Lyócsa, Š., Baumöhl, E., & Výrost, T. (2022). YOLO Trading: Riding with the Herd during the GameStop Episode. *Finance Research Letters*, *46*, 102359.

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the Coronavirus and the Stock Markets. *Finance research letters*, *36*, 101735.

Lyon, J. D., Barber, B. M., & Tsai, C. L. (1999). Improved Methods for Tests of Long-Run Abnormal Stock Returns. *The Journal of Finance*, *54*(1), 165-201.

Macciocchi, D., Lanini, S., Vairo, F., Zumla, A., Moraes Figueiredo, L. T., Lauria, F. N., Strada, G., Brouqui, P., Puro, V., Krishna, S., Kremsner, P., Scognamiglio, P., Köhler, C., Nicastri, E., Di Caro, A., Cieri, R. M., Ioannidis, J. P. A., Kobinger, G., Nascimento Burattini, M. & Ippolito, G. (2016). Short-term Economic Impact of the Zika Virus Outbreak. *New Microbiologica*, *39(4),* 287-289.

MacFarland, T. W., & Yates, J. M. (2016). *Mann–Whitney U Test.* Introduction to nonparametric Statistics for the biological Sciences using R, 103-132. Cham: Springer.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, *35*(1), 13-39.

Macrotrends. (n.d.). S&P 500 historical Annual Returns. Retrieved from: https://www.macrotrends.net/2526/sp-500-historical-annual-returns

Maknickiene, N., Lapinskaite, I., & Maknickas, A. (2018). Application of Ensemble of recurrent Neural Networks for forecasting of Stock Market Sentiments. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *13*(1), 7-27.

Malkiel, B. (1992), Efficient Market Hypothesis, in Eatwell, J., Milgate, M., & Newman, P. (Eds.). (1992). *The New Palgrave Dictionary of Money and Finance: 3 Volume Set*. Springer.

Malkiel, B. G. (1989). Efficient Market Hypothesis. In *Finance*, 127-134. London: Palgrave Macmillan UK.

Maneenop, S., & Kotcharin, S. (2020). The Impacts of COVID-19 on the Global Airline Industry: An Event Study Approach. *Journal of Air Transport Management*, *89*, 101920.

Mangee, N. (2018). Stock Returns and the one of Marketplace Information: Does Context matter?. *Journal of Behavioral Finance*, *19*(4), 396-406.

Mankiw, N. G. (1998). *Principles of microeconomics* (Vol. 1). Elsevier.

Mann, H. B., & Whitney, D. R. (1947). On a Test of whether one of two random Variables is stochastically larger than the other. In: *The Annals of Mathematical Statistics*, 50-60.

Mansfield, E. R., & Helms, B. P. (1982). Detecting Multicollinearity. *The American Statistician*, *36*(3a), 158-160. https://doi.org/10.1080/00031305.1982.10482818

Mao, H., Counts, S., & Bollen, J. (2011). Predicting financial markets: Comparing Survey, News, Twitter and Search Engine Data. *arXiv preprint arXiv:1112.1051*.

Markowitz, H. (1952). Portfolio Selection. The Journal of Finance 7(1), pp. 77-91.

Marshall, A. (2013). *Principles of Economics*. Springer.

Martins, A. M., & Cró, S. (2022). Airline Stock Markets Reaction to the COVID-19 Outbreak and Vaccines: An Event Study. *Journal of Air Transport Management*, *105*, 102281.

Masulis, R. W. (1980). The Effects of Capital Structure Change on Security Prices: A Study of Exchange Offers. *Journal of Financial Economics*, *8*(2), 139-178.

Mavragani, A., & Gkillas, K. (2020). COVID-19 Predictability in the United States using Google Trends Time Series. *Scientific reports*, *10*(1), 20693.

Mavragani, A., & Ochoa, G. (2019). Google Trends in Infodemiology and Infoveillance: Methodology Framework. *JMIR Public Health and Surveillance*, *5*(2), e13439.

Maziarz, M. (2015). A Review of the Granger-causality Fallacy. *The Journal of Philosophical Economics: Reflections on Economic and Social Issues*, *8*(2), 86-105.

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 Stock Market Crash. Evidence from S&P1500. *Finance research letters, 38,* 101690.

McCrorie, J. R., & Chambers, M. J. (2006). Granger causality and the Sampling of Economic Processes. *Journal of Econometrics*, *132*(2), 311-336.

McGurk, Z., Nowak, A., & Hall, J. C. (2020). Stock Returns and Investor Sentiment: Textual Analysis and Social Media. *Journal of Economics and Finance*, *44*(3), 458–485. https://doi.org/10.1007/s12197-019-09494-4

McKinsey & Company. (2021). *The Impact of COVID-19 on Capital Markets: One Year in*. Retrieved from: https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/the-impact-of-covid-19-on-capital-markets-one-year-in

McWilliams, A., & Siegel, D. (1997). Event Studies in Management Research: Theoretical and Empirical Issues. *Academy of Management Journal, 40 (3),* 626-657.

Mian, G. M., & Sankaraguruswamy, S. (2012). Investor Sentiment and Stock Market Response to Earnings News. *The Accounting Review*, *87*(4), 1357-1384.

Mili, M., Al Amoodi, A. Y., & Bawazir, H. (2024). The asymmetric Effect of COVID-19 on Investor Sentiment: Evidence from NARDL Model. *Review of Behavioral Finance*, *16*(1), 60-84.

Miller, S. (2020). *Theorie in Coronazeiten - Brennglas für gesellschaftliche Missstände*. Deutschlandfunk Kultur. Retrieved from: https://www.deutschlandfunkkultur.de/theorie-in-coronazeiten-brennglas-fuer-gesellschaftliche.2162.de.html?dram:article_id=479895

Mishkin, F. S., & White, E. N. (2003). US Stock Market Crashes and Their Aftermath: Implications for Monetary Policy. *Working Paper 8992* http://www.nber.org/papers/w8992

Mnasri, A., & Nechi, S. (2016). Impact of Terrorist Attacks on Stock Market Volatility in Emerging Markets. *Emerging Markets Review*, *28*, 184–202. https://doi.org/10.1016/j.ememar.2016.08.002

Modi, S. B., Wiles, M. A., & Mishra, S. (2015). Shareholder Value Implications of Service Failures in Triads: The Case of Customer Information Security Breaches. Journal of Operations Management, 35, 21-39.

Moe, T. M. (1982). Regulatory Performance and Presidential Administration. American Journal of Political Science, 197-224.

Monash. (2018). *Hedonic Demand Theory.* Monash Business School. Retrieved from: https://www.monash.edu/business/marketing/marketing-dictionary/h/hedonic-demand-theory

Moog, P. (2013). *Rahmenbedingungen & Grundprinzipien wirtschaftlichen Handelns*. Retrieved from: https://www.wiwi.uni-siegen.de/business-succession/lehre/lehrveranstaltungen/sommersemster/sommersemester2013/ringvorlesung/orientierungsmodulm1_ringvorlesungsos2013.pdf

Mossin, J. (1966). Equilibrium in a Capital Asset Market. Econometrica: Journal of the Econometric Society, 768-783.

MSCI. (2023). *GICS® framework reclassification 2023: Transcript*. Retrieved from: https://www.msci.com/documents/1296102/38146359/GICS%C2%AE+Framework+Reclassification+2023+-+Transcript.pdf

Murphy, J. J. (1999). *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*. Penguin.

Musleh Alsartawi, A., Hegazy, M. A. A., & Hegazy, K. (2022). Guest Editorial: the COVID-19 Pandemic: a Catalyst for Digital Transformation. *Managerial Auditing Journal*, *37(7),* 769-774.

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica: Journal of the Econometric Society*, 315-335.

Nachar, N. (2008). The Mann-Whitney U: A Test for assessing whether two independent Samples come from the same Distribution. *Tutorials in quantitative Methods for Psychology*, *4(1),* 13-20.

Nasdaq (2020). *The Fear of Missing Out.* Retrieved from: https://www.nasdaq.com/articles/the-fear-of-missing-out-2020-06-10

Neal, R., & Wheatley, S. M. (1998). Do Measures of Investor Sentiment Predict Returns? *The Journal of Financial and Quantitative Analysis*, *33*(4), 523. https://doi.org/10.2307/2331130

Nelson, W. R. (1999). Three Essays on the Ability of the Change in Shares Outstanding to Predict Stock Returns. Yale University.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M. & Agha, R. (2020). The socio-economic Implications of the Coronavirus Pandemic (COVID-19): A review. *International Journal of Surgery, 78,* 185-193.

Nikkinen, J., Omran, M. M., Sahlström, P., & Äijö, J. (2008). Stock Returns and Volatility following the September 11 Attacks: Evidence from 53 Equity Markets. *International Review of Financial Analysis*, *17(1),* 27-46.

Nikkinen, J., Piljak, V., & Äijö, J. (2012). Baltic Stock Markets and the Financial Crisis of 2008–2009. *Research in International Business and Finance*, *26*(3), 398-409.

Nippani, S., & Washer, K. M. (2004). SARS: A Non-Event for Affected Countries' Stock Markets? *Applied Financial Economics*, *14*(15), 1105–1110. https://doi.org/10.1080/0960310042000310579

Noy, I., & Nualsri, A. (2007). *What do exogenous Shocks tell us about Growth Theories?* Working paper.

Odean, T. (1998). Volume, Volatility, Price, and Profit when all Traders are above Average. *The Journal of Finance*, *53*(6), 1887-1934.

Oler, D. K., Harrison, J. S., & Allen, M. R. (2008). The Danger of misinterpreting Short-Window Event Study Findings in Strategic Management Research: An empirical Illustration using horizontal Acquisitions. *Strategic Organization*, *6(2),* 151-184.

Pagano, M. (1989). Trading Volume and Asset Liquidity. *The Quarterly Journal of Economics, 104*(2), 255-274.

Page, T. F., Williams, M. L., Cassella, G., Amick, B. C., & Adler, J. L. (2017). The Impact of Zika on Local Businesses. *Disaster Prevention and Management*, *26*(4), 452–457. https://doi.org/10.1108/DPM-04-2017-0090

Pagnottoni, P., Spelta, A., Flori, A., & Pammolli, F. (2022). Climate Change and financial Stability: Natural Disaster Impacts on global Stock Markets. *Physica A: Statistical Mechanics and Its Applications*, *599*, 127514.

Pandey, D. K., & Kumari, V. (2021). Event Study on the Reaction of the developed and emerging Stock Markets to the 2019-nCoV Outbreak. *International Review of Economics & Finance*, *71*, 467-483.

Pandey, D. K., Kumari, V., Palma, A., & Goodell, J. W. (2024). Are Markets in happier Countries less affected by tragic Events? Evidence from Market Reaction to the Israel–Hamas Conflict. *Finance Research Letters*, *60*, 104893.

Papakyriakou, P., Sakkas, A., & Taoushianis, Z. (2019). The Impact of Terrorist Attacks in G7 Countries on International Stock Markets and the Role of Investor Sentiment. *Journal of International Financial Markets, Institutions and Money*, *61*, 143-160.

Pareto, V. (1919). *Manuale di Economia Politica con una Introduzione alla Scienza Sociale* (Vol. 13). Società editrice libraria.

Patel, J., Zeckhauser, R., & Hendricks, D. (1991). The Rationality Struggle: Illustrations from Financial Markets. *The American Economic Review*, *81*(2), 232-236.

Pauser, S. (2008). Determinanten erfolgreicher M&A-Transaktionen in der Bauindustrie. In *M&A in der Bauindustrie*, 161–216. Gabler. https://doi.org/10.1007/978-3-8350-5543-8_6

Peleg, K., Regens, J. L., Gunter, J. T., & Jaffe, D. H. (2011). The Normalisation of Terror: the Response of Israel's Stock Market to Long Periods of Terrorism. *Disasters*, *35*(1), 268–283. https://doi.org/10.1111/j.1467-7717.2010.01203.x

Pendell, D. L., & Cho, C. (2013). Stock Market Reactions to Contagious Animal Disease Outbreaks: An Event Study in Korean Foot-and-Mouth Disease Outbreaks. *Agribusiness*, *29*(4), 455-468. https://doi.org/10.1002/agr.21346

Pham, Q., Pham, H., Pham, T., & Tiwari, A. K. (2025). Revisiting the role of investor sentiment in the stock market. *International Review of Economics and Finance*, *100*. https://doi.org/10.1016/j.iref.2025.104089

Phuong, L. (2020). Investor Sentiment by Psychological Line Index and Stock Return. *Accounting*, *6*(7), 1259-1264.

Phuong, L. (2021). Investor Sentiment by Relative Strength Index and Stock Return: Empirical Evidence on Vietnam's Stock Market. *Accounting, 7*(2), 451-456.

Phylaktis, K., & Xia, L. (2006). The changing Roles of Industry and Country Effects in the Global Equity Markets. *The European Journal of Finance*, *12*(8), 627-648.

Piccoli, P., da Costa Jr, N. C., da Silva, W. V., & Cruz, J. A. (2018). Investor Sentiment and the Risk–Return Tradeoff in the Brazilian Market. *Accounting & Finance*, *58*, 599-618.

Piepenbrock, D. (n.d.). *Mikroökonomik • Definition | Gabler Wirtschaftslexikon*. Retrieved from https://wirtschaftslexikon.gabler.de/definition/mikrooekonomik-39342

Pizarro, J. M., Chermak, S. M., & Gruenewald, J. A. (2007). Juvenile "Super-Predators" in the News: A Comparison of Adult and Juvenile Homicides. *Journal of Criminal Justice and Popular Culture*, *14*(1), 84-111.

Psychological Line | Charts Help and Tutorials. (2021). Retrieved May 6, 2021, from https://library.tradingtechnologies.com/trade/chrt-ti-psychological-line.html

Qiu, L., & Welch, I. (2004). *Investor Sentiment Measures*. https://www.nber.org/papers/w10794

Rahman, M. L., Amin, A., & Al Mamun, M. A. (2021). The COVID-19 Outbreak and Stock Market Reactions: Evidence from Australia. *Finance Research Letters*, *38*, 101832. https://doi.org/10.1016/j.frl.2020.101832

Rehse, D., Riordan, R., Rottke, N., & Zietz, J. (2019). The Effects of Uncertainty on Market Liquidity: Evidence from Hurricane Sandy. *Journal of Financial Economics*, *134*(2), 318–332. https://doi.org/10.1016/j.jfineco.2019.04.006

Reis, P., & Pinho, C. (2020). *COVID-19 and Investor Sentiment Influence on the US and European Countries Sector Returns*. https://europepmc.org/article/ppr/ppr243293

Ritter, J. R. (1991). The Long-Run Performance of Initial Public Offerings. *The Journal of Finance*, *46*(1), 3–27. https://doi.org/10.1111/j.1540-6261.1991.tb03743.x

Rjoub, S. A. M. Al. (2011). Before the Crises: Implication for the US Stock Market. *International Journal of Trade and Global Markets*, *4*(1), 1. https://doi.org/10.1504/ijtgm.2011.037885

Roberts, H. V. (1959). Stock-Market "Patterns" and Financial Analysis: Methodological Suggestions. *The Journal of Finance*, *14*(1), 1-10.

Roberts, H. V. (1967). Statistical versus clinical Prediction of the Stock Market. *Unpublished Manuscript*, *252*.

Robinson, C. J., & Bangwayo-Skeete, P. (2016). The Financial Impact of Natural Disasters: Assessing the Effect of Hurricanes & Tropical Storms on Stock Markets in the Caribbean. *Available at SSRN 2845429*.

Roßbach, P. (2001). *Behavioral Finance: eine Alternative zur vorherrschenden Kapitalmarkttheorie?* (No. 31). Arbeitsberichte der Hochschule für Bankwirtschaft.

Rossi, M. (2016). The Capital Asset Pricing Model: A Critical Literature Review. *Global Business and Economics Review*, *18*(5), 604-617.

Rozeff, M. S., & Kinney, W. R. (1976). Capital Market Seasonality: The Case of Stock Returns. *Journal of Financial Economics, 3*(4), 379-402.

Rupande, L., Muguto, H. T., & Muzindutsi, P. F. (2019). Investor Sentiment and Stock Return Volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*.

Ryu, D., Kim, H., & Yang, H. (2017). Investor Sentiment, Trading Behavior and Stock Returns. *Applied Economics Letters*, *24*(12), 826–830. https://doi.org/10.1080/13504851.2016.1231890

Ryu, D., Ryu, D., & Yang, H. (2019). Investor Sentiment, Market Competition, and Financial Crisis: Evidence from the Korean Stock Market. *Emerging Markets Finance and Trade*, *56*(8), 1804-1816.

S&P Global. (2023). The S&P 500 and the Dow: What's the Difference?. Retrieved from: https://www.spglobal.com/spdji/en/research-insights/index-literacy/the-sp-500-and-the-dow/

Salisu, A. A., & Akanni, L. O. (2020a). Constructing a Global Fear Index for the COVID-19 Pandemic. *Emerging Markets Finance and Trade*, *56*(10), 2310–2331. https://doi.org/10.1080/1540496X.2020.1785424

Salisu, A. A., Akanni, L., & Raheem, I. (2020b). The COVID-19 global fear index and the predictability of commodity price returns. *Journal of Behavioral and Experimental Finance*, *27*, 100383.

Samuelson, P. A. (1948). Consumption Theory in Terms of Revealed Preference. *Economica*, *15*(60), 243-253.

Samuelson, Paul A. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, *6*(2): 41-49.

Samuelson, Paul A. (1973). Proof That Properly Discounted Present Values of Assets Vibrate Randomly. *Bell Journal of Economics*, *4*(2): 369-374.

Sanger, G. C., & Peterson, J. D. (1990). An empirical Analysis of common Stock Delistings. *Journal of Financial and Quantitative Analysis, 25(2),* 261-272.

Sanger, G. C., & Peterson, J. D. (1990). An empirical Analysis of common Stock Delistings. *Journal of Financial and Quantitative Analysis, 25*(2), 261-272.

Sapkota, N. (2022). News-based Sentiment and Bitcoin Volatility. *International Review of Financial Analysis*, *82*, 102183.

Saunders Jr., E. (1993). Stock Prices and the Wall Street Weather. *American Economic Review*, *83*(5), 1337–1345. https://doi.org/10.2307/2117565

Savickas, R. (2003). Event-induced Volatility and Tests for Abnormal Performance. *Journal of Financial Research*, *26*(2), 165-178.

Sayed, O. A., & Eledum, H. (2023). The Short-Run Response of Saudi Arabia Stock Market to the Outbreak of COVID-19 Pandemic: An Event-Study Methodology. *International Journal of Finance & Economics*, *28*(3), 2367-2381.

Scheinkman, J. A., & Xiong, W. (2003). Overconfidence and speculative Bubbles. *Journal of Political Economy*, *111*(6), 1183-1220.

Schmeling, M. (2009). Investor Sentiment and Stock Returns: Some International Evidence. *Journal of Empirical Finance*, *16*(3), 394-408.

Scholtens, B., & Peenstra, W. (2009). Scoring on the Stock Exchange? The Effect of Football Matches on Stock Market Returns: An Event Study. *Applied Economics*, *41*(25), 3231–3237. https://doi.org/10.1080/00036840701721406

Sehgal, S., Sood, G. S., & Rajput, N. (2009). Investor Sentiment in India: A Survey. *Vision*, *13*(2), 13-23.

Seok, S. I., Cho, H., & Ryu, D. (2019a). Firm-specific Investor Sentiment and Daily Stock Returns. *North American Journal of Economics and Finance*, *50*. https://doi.org/10.1016/j.najef.2018.10.005

Seok, S. I., Cho, H., & Ryu, D. (2019b). Firm-specific Investor Sentiment and the Stock Market Response to Earnings News. *North American Journal of Economics and Finance*, *48*, 221–240. https://doi.org/10.1016/j.najef.2019.01.014

Seok, S. I., Cho, H., & Ryu, D. (2021). Stock Market's Responses to Intraday Investor Sentiment. *The North American Journal of Economics and Finance*, *58*, 101516.

Seok, S. I., Cho, H., & Ryu, D. (2022). Scheduled Macroeconomic News Announcements and Intraday Market Sentiment. *The North American Journal of Economics and Finance*, *62*, 101739.

Seok, S. I., Cho, H., & Ryu, D. (2024). Dual Effects of Investor Sentiment and Uncertainty in Financial Markets. *The Quarterly Review of Economics and Finance*, *95*, 300-315.

Seok, S. I., Cho, H., Park, C., & Ryu, D. (2019c). Do Overnight Returns Truly Measure Firm-Specific Investor Sentiment in the KOSPI Market? *Sustainability (Switzerland)*, *11*(13). https://doi.org/10.3390/su11133718

Serra, A. P. (2004). Event Study Tests: A Brief Survey. Gestão. *Org-Revista Electrónica de Gestão Organizacional, 2*(3), 248-255.

Sewell, M. (2011). History of the Efficient Market Hypothesis. *Research Note*, 11(04).

Shaikh, I. (2021). Impact of COVID-19 Pandemic Disease Outbreak on the Global Equity Markets. *Economic Research-Ekonomska Istraživanja*, *34*(1), 2317-2336.

Shapiro, A. H., Sudhof, M., & Wilson, D. J. (2022). Measuring News Sentiment. *Journal of Econometrics*, *228*(2), 221-243.

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika, 52*(3-4), 591-611.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence from the Wavelet-based Approach. *International Review of Financial Analysis*, *70*, 101496.

Sharma, S. S., Narayan, P. K., & Zheng, X. (2014). An Analysis of Firm and Market Volatility. *Economic Systems*, *38*(2), 205–220. https://doi.org/10.1016/j.ecosys.2013.12.003

Sharpe, W. F. (1963). A Simplified Model for Portfolio Analysis. *Management Science*, *9*(2), 277-293.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sharpe, W. F. (1970). *Portfolio Theory and Capital Markets*. New York: McGraw-Hill.

Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19's Disasters are perilous than Global Financial Crisis: A Rumor or Fact?. *Finance Research Letters*, 36, 101669.

Shen, S., Xia, L., Shuai, Y., & Gao, D. (2022). Measuring News Media Sentiment using Big Data for Chinese Stock Markets. *Pacific-Basin Finance Journal*, 74, 101810.

Shiller, R. (1999). *Results of Surveys about Stock Market Speculation 12/99*. Retrieved from: http://www.econ.yale.edu/~shiller/data/investor.html

Shiller, R. J. (1981). *Do Stock Prices move too much to be justified by subsequent Changes in Dividends*? Cambridge: National Bureau of Economic Research,

Shiller, R. J. (2015). *Irrational Exuberance: Revised and Expanded third Edition*. Princeton University Press.

Shiller, R. J., Fischer, S., & Friedman, B. M. (1984). Stock Prices and Social Dynamics. *Brookings Papers on Economic Activity*, *1984*(2), 457. https://doi.org/10.2307/2534436

Shleifer, A., & Summers, L. H. (1990). The Noise Trader Approach to Finance. *Journal of Economic Perspectives*, *4*(2), 19–33. https://doi.org/10.1257/jep.4.2.19

Shojaie, A., & Fox, E. B. (2022). Granger Causality: A Review and Recent Advances. *Annual Review of Statistics and Its Application*, *9*(1), 289-319.

Sibande, X., Gupta, R., Demirer, R., & Bouri, E. (2023). Investor Sentiment and (anti) Herding in the Currency Market: Evidence from Twitter Feed Data. *Journal of Behavioral Finance*, *24*(1), 56-72.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2017). Divergence of Sentiment and Stock Market Trading. *Journal of Banking and Finance*, *78*, 130–141. https://doi.org/10.1016/j.jbankfin.2017.02.005

Simon, H. A. (1955). A behavioral Model of rational Choice. *The Quarterly Journal of Economics*, 99-118.

Simon, H. A. (1972). Theories of Bounded Rationality. *Decision and Organization*, *1*(1), 161-176.

Simon, H. A. (1986). Rationality in Psychology and Economics. *Journal of Business*, 209-224.

Sims, C. A. (1972). Money, Income, and Causality. *The American Economic Review*, *62*(4), 540-552.

Singh, B., Dhall, R., Narang, S., & Rawat, S. (2024). The Outbreak of COVID-19 and Stock Market Responses: An Event Study and Panel Data Analysis for G-20 Countries. *Global Business Review*, *25*(3), 606-631.

Skidmore, M., & Toya, H. (2002). Do Natural Disasters promote long-run Growth?. *Economic Inquiry*, *40*(4), 664-687.

Slone, M. (2000). Responses to Media Coverage of Terrorism. *Journal of Conflict Resolution*, *44*(4), 508–522. https://doi.org/10.1177/0022002700044004005

Smales, L. A. (2014). News Sentiment in the Gold Futures Market. *Journal of Banking & Finance*, *49*, 275-286.

Smith, A. (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations: Volume One*. London: Printed Strahan Cadell, 1776.

Snarska, M., Frydrych, S., Łukowski, M., Czech, M., & Perez, K. (2025). Semiconductor game of thrones: A comprehensive study of geopolitical and equity market uncertainty transmission. *International Review of Financial Analysis*, 106, 104457. https://www.sciencedirect.com/science/article/pii/S1057521925005447

So, S. M., & Lei, V. U. (2015). On the Relationship between Investor Sentiment, VIX and Trading Volume. *Risk Governance & Control: Financial Markets & Institutions*, *5*(4), 114-122.

Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., ... & Agha, R. (2020). World Health Organization Declares Global Emergency: A Review of the 2019 Novel Coronavirus (COVID-19). *International Journal of Surgery*, *76*, 71-76.

Stigler, G. J. (1961). The Economics of Information. *Journal of Political Economy, 69*(3), 213-225.

Stiglitz, J. E. (2002). Information and the Change in the Paradigm in Economics. *American Economic Review*, *92*(3), 460-501.

Stiglitz, J., & Grossman, S. (1982). On the Impossibility of Informationally Efficient Markets: Reply. *The American Economic Review*, *72*(4), 875–875. https://doi.org/10.7916/D8N87MRN

Strategische Unternehmensplanung. (2020). Retrieved December 28, 2020, from https://www.controllingportal.de/Fachinfo/Finanzplanung/Strategische-Unternehmensplanung.html

Su, Z., Fang, T., & Yin, L. (2019). Understanding Stock Market Volatility: What is the Role of US Uncertainty?. *The North American Journal of Economics and Finance*, *48*, 582-590.

Sun, L., & Shi, W. (2022). Investor Sentiment and Stock Market Reactions to COVID-19: Evidence from China. *Discrete Dynamics in Nature and Society*, *2022*(1), 8413916.

Sun, L., Najand, M., & Shen, J. (2016). Stock Return Predictability and Investor Sentiment: A High-Frequency Perspective. *Journal of Banking & Finance*, *73*, 147-164.

Sun, Y., Wu, M., Zeng, X., & Peng, Z. (2021). The Impact of COVID-19 on the Chinese Stock Market: Sentimental or Substantial?. *Finance Research Letters*, *38*, 101838.

Taleb, N. N. (2010). *The Black Swan: The Impact of the Highly Improbable: With a new Section:" On Robustness and Fragility" (Vol. 2)*. Random House Trade Paperbacks.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance*, *62*(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x

Thadewald, T., & Büning, H. (2007). Jarque–Bera Test and Its Competitors for Testing Normality–a Power Comparison. *Journal of Applied Statistics, 34*(1), 87-105.

Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, *4*(3), 199-214.

Thaler, R. H. (Ed.). (2005). *Advances in Behavioral Finance, Volume II*. Princeton University Press.

Thompson, R. (1995). Empirical Methods of Event Studies in Corporate Finance. In *Handbooks in Operations Research and Management Science*, 9(C), 963–992. https://doi.org/10.1016/S0927-0507(05)80073-8

Tinbergen, J. (1956). *On the Theory of Income Distribution.* Amsterdam, North Holland. https://www.jstor.org/stable/40435398

Tischer, S., & Hildebrandt, L. (2014). Linking Corporate Reputation and Shareholder Value using the Publication of Reputation Rankings. *Journal of Business Research, 67*(5), 1007-1017.

Tomer, J. F. (2001). Economic Man vs. Heterodox Men: the Concepts of Human Nature in Schools of Economic Thought. *The Journal of Socio-Economics*, *30*(4), 281–281.

Topcu, M., & Gulal, O. S. (2020). The Impact of COVID-19 on Emerging Stock Markets. *Finance Research Letters, 36*, 101691. https://go.gale.com/ps/i.do?p=AONE&sw=w&issn=10535357&v=2.1&it=r&id=GALE%7CA79355201&sid=googleScholar&linkaccess=fulltext

Tsuchiya, Y. (2021). Crises, Market Shocks, and Herding Behavior in Stock Price Forecasts. *Empirical Economics*, *61*(2), 919-945.

Turtle, H. J., & Wang, K. (2017). *The Value in Fundamental Accounting Information*. In Wiley Online Library (Vol. 40, Issue 1). Blackwell Publishing Ltd. https://doi.org/10.1111/jfir.12119

Tweneboah-Koduah, S., Atsu, F., & Prasad, R. (2020). Reaction of Stock Volatility to Data Breach: An Event Study. *Journal of Cyber Security and Mobility,* 355-384.

Tye, M. (1997). *Ten Problems of Consciousness: A Representational Theory of the Phenomenal Mind*. MIT Press. https://books.google.com/books?hl=de&lr=&id=L6QMP6LaPckC&oi=fnd&pg=P

R11&dq=Ten+problems+of+consciousness:+A+representational+theory+of+the+phenomenal+mind.+mit+Press,+1995&ots=sdBmLIqf8t&sig=PqlTG-Y_1erdOZGtUIl4lpatPMw

Ullah, S., Zaefarian, G., Ahmed, R., & Kimani, D. (2021). How to Apply the Event Study Methodology in STATA: An Overview and a Step-by-Step Guide for Authors. *Industrial marketing management*, *99*, A1-A12.

Ung, S. N., Gebka, B., & Anderson, R. D. J. (2024). An enhanced investor sentiment index. *European Journal of Finance*, *30*, 827–864. https://doi.org/10.1080/1351847X.2023.2247440

United Nations. (2023). *WHO Chief Declares End to COVID-19 as a Global Health Emergency*. United Nations News. Retrieved from: https://news.un.org/en/story/2023/05/1136367

Vasterman, P., Yzermans, C. J., & Dirkzwager, A. J. E. (2005). The Role of the Media and Media Hypes in the Aftermath of Disasters. *Epidemiologic Reviews*, 27, 107–114. https://doi.org/10.1093/epirev/mxi002

Velavan, T. P., & Meyer, C. G. (2020). The COVID-19 Epidemic. *Tropical Medicine & International Health, 25(*3), 278.

Verma, R., Baklaci, H., & Soydemir, G. (2008). The Impact of rational and irrational Sentiments of individual and institutional Investors on DJIA and S&P500 Index Returns. *Applied Financial Economics, 18*(16), 1303-1317.

Von Neumann, J., & Morgenstern, O. (2007). *Theory of Games and Economic Behavior. 60th Anniversary Commemorative Edition.* Princeton NJ, Princeton University Press.

Walther, B. R., & Willis, R. H. (2013). Do Investor Expectations Affect Sell-Side Analysts' Forecast Bias and Forecast Accuracy? *Review Accounting Studies*, *18*, 207–227. https://doi.org/10.1007/s11142-012-9204-9

Wang, F. A. (2001). Overconfidence, Investor Sentiment, and Evolution. *Journal of Financial Intermediation, 10*(2), 138-170.

Wang, G. J., Xie, C., Wen, D., & Zhao, L. (2019). When Bitcoin meets economic Policy Uncertainty (EPU): Measuring Risk Spillover Effect from EPU to Bitcoin. *Finance Research Letters*, *31*, 489–497. https://doi.org/10.1016/j.frl.2018.12.028

Wang, L., & Kutan, A. M. (2013). The Impact of Natural Disasters on Stock Markets: Evidence from Japan and the US. *Comparative Economic Studies*, *55*(4), 672–686. https://doi.org/10.1057/ces.2013.16

Wang, P., Li, X., Shen, D., & Zhang, W. (2020). How does Economic Policy Uncertainty affect the Bitcoin Market? *Research in International Business and Finance*, *53*. https://doi.org/10.1016/j.ribaf.2020.101234

Wang, Q., & Ngai, E. W. (2020). Event Study Methodology in Business Research: a Bibliometric Analysis. *Industrial Management & Data Systems*, *120*(10), 1863-1900.

Wang, W., Su, C., & Duxbury, D. (2021). Investor Sentiment and Stock Returns: Global Evidence. *Journal of Empirical Finance*, *63*, 365-391.

Wen, F. He, Z., Dai, Z., & Yang, X. (2014). Characteristics of Investors' Risk Preference for Stock Markets. *Economic Computation & Economic Cybernetics Studies & Research*, *48*(3).

Wheeler, D. J. (2004). *Advanced Topics in Statistical Process Control : The Power of Shewhart's Charts*. 470. SPC Press. Knoxville, Tennessee. https://books.google.com/books/about/Advanced_Topics_in_Statistical_Process_C.html?hl=de&id=63EePQAACAAJ

Widmaier, W. W., Blyth, M., & Seabrooke, L. (2007). Exogenous Shocks or Endogenous Constructions? The Meanings of Wars and Crises. *International Studies Quarterly, 51*(4), 747-759.

Williams, L. V. (1999). Information Efficiency in Betting Markets: A Survey. *Bulletin of Economic Research*, *51*(1), 1-39.

Wirtschaftslexikon24. (2020). *Aktienkurs - Wirtschaftslexikon*. Retrieved from: http://www.wirtschaftslexikon24.com/d/aktienkurs/aktienkurs.htm

Wolf, H. C. (1998). *Determinants of Emerging Market Correlations*. In Emerging Market Capital Flows: Proceedings of a Conference held at the Stern School of Business, New York University on May 23–24, 1996, 219-235. Boston: Springer US.

Woo, K. Y., Mai, C., McAleer, M., & Wong, W. K. (2020). Review on Efficiency and Anomalies in Stock Markets. *Economies*, *8*(1), 20.

World Bank. 2020). *Commodity Markets Outlook: Special Focus.* Retrieved from: https://www.worldbank.org/en/research/commodity-markets

World Health Organisation (WHO) (2020). Listings of WHO's Response to COVID-19. Retrieved from: https://www.who.int/news/item/29-06- 2020-covidtimeline

World Health Organization (2020). Novel Coronavirus (2019-nCov) Situation Report 2. Retrieved from: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200122-sitrep-2-2019-ncov.pdf?sfvrsn=4d5bcbca_2

World Health Organization (2020). *WHO/Europe | Coronavirus Disease (COVID-19) Outbreak - WHO announces COVID-19 Outbreak a Pandemic*. Retrieved from: https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic

World Health Organization (2024). *COVID Cases and Deaths*. Retrieved from: https://data.who.int/dashboards/covid19/deaths?n=c

Wu, G., Yang, B., & Zhao, N. (2020). Herding Behavior in Chinese Stock Markets during COVID-19. *Emerging Markets Finance and Trade*, *56*(15), 3578-3587.

Wu, S. J., & Lee, W. M. (2015). Intertemporal Risk–Return Relationships in Bull and Bear Markets. *International Review of Economics & Finance*, *38*, 308-325.

Xu, Q., Chang, V., & Hsu, C. H. (2020). Event Study and Principal Component Analysis Based on Sentiment Analysis – A Combined Methodology to Study the Stock Market with an Empirical Study. *Information Systems Frontiers*, *22*(5), 1021–1037. https://doi.org/10.1007/s10796-020-10024-5

Yahoo Finance. (2020). *S&P 500 (^GSPC) Historical Data*. Retrieved from: https://finance.yahoo.com/quote/%5EGSPC/history/

Yang, C., & Chi, J. (2021). Investor Sentiment and Volatility of Exchange-Traded Funds: Evidence from China. *International Journal of Finance & Economics*, ijfe.2443. https://doi.org/10.1002/ijfe.2443

Yang, C., & Gao, B. (2014). The Term Structure of Sentiment Effect in Stock Index Futures Market. *North American Journal of Economics and Finance*, *30*, 171–182. https://doi.org/10.1016/j.najef.2014.09.001

Yang, C., & Zhang, R. (2014). Does Mixed-Frequency Investor Sentiment Impact Stock Returns? Based on the Empirical Study of MIDAS Regression Model. *Applied Economics*, *46*(9), 966–972. https://doi.org/10.1080/00036846.2013.864041

Yang, C., & Zhou, L. (2015). Investor Trading Behavior, Investor Sentiment and Asset Prices. *North American Journal of Economics and Finance*, *34*, 42–62. https://doi.org/10.1016/j.najef.2015.08.003

Yang, H., Ryu, D., & Ryu, D. (2017). Investor Sentiment, Asset Returns and Firm Characteristics: Evidence from the Korean Stock Market. *Investment Analysts Journal*, *46*(2), 132–147. https://doi.org/10.1080/10293523.2016.1277850

Yao, C. Z., & Li, H. Y. (2020). Time-varying Lead–Lag Structure between Investor Sentiment and Stock Market. *North American Journal of Economics and Finance*, *52*, 101148. https://doi.org/10.1016/j.najef.2020.101148

Yilmazkuday, H. (2023). COVID-19 Effects on the S&P 500 Index. *Applied Economics Letters, 30*(1), 7-13.

Yu, J., & Yuan, Y. (2011). Investor Sentiment and the Mean–Variance Relation. *Journal of Financial Economics*, *100*(2), 367-381.

Yu, J., Huang, H. H., & Hsu, S. W. (2014). Investor Sentiment Influence on the Risk-Reward Relation in the Taiwan Stock Market. *Emerging Markets Finance and Trade*, *50*(2), 174-188.

Yuan, K., Zheng, L., & Zhu, Q. (2006). Are Investors moonstruck? Lunar Phases and Stock Returns. *Journal of Empirical Finance*, *13*(1), 1-23. https://doi.org/10.1016/j.jempfin.2005.06.001

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters*, *35*, 101597.

Zeitun, R., Rehman, M. U., Ahmad, N., & Vo, X. V. (2023). The Impact of Twitter-based Sentiment on US Sectoral Returns. *The North American Journal of Economics and Finance*, *64*, 101847.

Zhai, H., Xiao, M., Chan, K. C., & Liu, Q. (2022). Physical Proximity, Corporate Social Responsibility, and the Impact of Negative Investor Sentiment on Stock Returns: Evidence from COVID-19 in China. *International Review of Finance*, *22*(2), 308-314. https://doi.org/10.1111/irfi.12343

Zhou, G. (2018). Measuring Investor Sentiment. *Annual Review of Financial Economics, 10*(1), 239-259.

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does Investor Sentiment affect Stock Market Crises? Evidence from Panel Data. *Financial Review*, *46*(4), 723–747. https://doi.org/10.1111/j.1540-6288.2011.00318.x

Zweig, M. E. (1973). An Investor Expectations Stock Price Predictive Model Using Closed-End Fund Premiums. *The Journal of Finance*, *28*(1), 67-78.

LIST OF TABLES

LIST OF FIGURES

APPENDIX A. SUMMARY OF RESEARCH QUESTIONS, RELATED HYPOTHESES AND STAGES OF THE EMPIRICAL STUDY

Research Questions	Type of the RQ	Related Chapters	Related Hypotheses	Stages of the Empirical Study
RQ1: What are the theoretical foundations of the research problem?	Exploratory	2.1*; 2.2*; 2.3*; 2.4*;	-	-
RQ2: What are the results of previous studies concerning the research problem?	Exploratory	2.3*; 2.4*; 2.5*; 2.6*;	-	-
RQ3: What are the most suitable methods of measuring investor sentiment on a daily and company-specific basis?	Exploratory	2.4*; 4.1*; 6.2.1*	-	-
RQ4: Is investor sentiment measured using a market-based approach a reliable predictor of future security performance?	Explanatory	3.1; 4.3; 5.1.3; 6.2*	H1: The Overall Sentiment Indicator is capable of predicting the daily returns of the S&P 500 index. (Predictive Hypothesis)	Stage 1 - Determination of the company-specific sentiment indicators - Determination of the sector-based sentiment indicators - Determination of the aggregated overall sentiment indicator - Testing the OSI for predictive accuracy for daily stock returns.
RQ5: What is a suitable method for investigating the role of investor sentiment in moderating the impact of exogenous shocks on stock prices?	Exploratory	4.2*	-	-
RQ6: How do exogenous shocks, like the COVID-19 pandemic, impact investor sentiment, stock prices, and stock price volatility	Explanatory	3.2 4.4 5.1 5.2 6.1	H2a: The disclosure of the first COVID-19 case in the US leads to negative abnormal returns on stocks of companies included in the S&P 500 index. H2b: The declaration of the COVID-19 outbreak as a public health emergency in the US (American Hospital Association	Stage 2 - Investigation of the impact of the defined events on stock prices - Determination of CARs

across companies and industry sectors?		6.3*	2020) leads to negative abnormal returns on stocks of companies included in the S&P 500 index. H2c: The World Health Organization's declaration of a pandemic leads to negative abnormal returns on stocks of companies included in the S&P 500 index. (Return Hypotheses)	
		3.3 4.5 5.3 6.4*	H3a: The disclosure of the first COVID-19 case in the US a has an effect on stock price volatility for companies included in the S&P 500 index. H3b: The declaration of the COVID outbreak as a public health emergency in the US (American Hospital Association 2020) has an effect on the stock price volatility of companies included in the S&P 500 index. H3c: The World Health Organization's declaration of the pandemic has an effect on the stock price volatility of companies included in the S&P 500 index. (Volatility Hypotheses)	Stage 3 - Investigation of the impact of the defined events on stock price volatility
RQ7: What is the role of investor sentiment in stock prices' changes during the COVID-19 pandemic outbreak?	Explanatory	3.4 5.4* 6.5*	H4a: Investor sentiment moderates the relationship between the release of information about the first COVID-19 case and the stock prices of companies included in the S&P 500 index. H4b: Investor sentiment moderates the relationship between the release of information about the declaration of the COVID outbreak as a public health emergency in the US (American Hospital Association, 2020) and the stock prices of companies included in the S&P 500 index. H4c: Investor sentiment moderates the relationship between the release of information about the declaration of the pandemic by the World Health Organization and the stock prices of companies included in the S&P 500 index. (Moderating Effect Hypotheses)	Stage 4 - Investigation of the role of investor sentiment in the development of CARs during the defined events.
RQ8: Are there any patterns in investor response to pandemic-related events?	Exploratory	6.1.3* 6.1.4* 6.3.2*	-	-

Notes: * Chapters answering RQs; RQ1, RQ2, RQ3, RQ5, and RQ8 are intended to be exploratory in nature and therefore do not require hypotheses. RQ4, RQ,6, and RQ7 are explanatory, necessitating quantitative analysis and corresponding hypotheses that can be statistically tested.

APPENDIX B. LIST OF EXCLUDED COMPANIES AND REASONS OF EXCLUSIONS

Ticker	Company Name	Reasons for Exclusion	Source
AOS	A. O. Smith	April, 15 2020: Change in CEO / chairman / board members	https://investor.aosmith.com/news-releases/news-release-details/ajita-rajendra-retire-executive-chairman-o-smith-corporation
ABBV	AbbVie	incomplete data set / data not fully available / data quality issue	
ACN	Accenture	January, 13 2020: Other: Accenture Announces Changes to Its Growth Model and Global Management Committee	https://otp.tools.investis.com/clients/us/accenture2/SEC/sec-show.aspx?FilingId=13842294&Cik=0001467373&Type=PDF&hasPdf=1
AAP	Advance Auto Parts	March, 4 2020: Change in CEO / chairman / board members	https://d18rn0p25nwr6d.cloudfront.net/CIK-0001158449/576dd1a9-7663-4c45-a3ef-20f79b4b3234.pdf
AFL	Aflac	December, 27th 2019: Lawsuit / compliance issue	https://d18rn0p25nwr6d.cloudfront.net/CIK-0000004977/ff2c104a-043c-43a9-869c-514481956e09.pdf
ALB	Albemarle Corporation	February, 5th 2020: Change in CEO / chairman / board members	https://d18rn0p25nwr6d.cloudfront.net/CIK-0000915913/8a726446-bf0a-49c7-a478-a0900e5adc03.pdf
MO	Altria	January, 31st 2020: Other: Altria Takes a $4.1 Billion Hit on Juul Stake	https://www.nytimes.com/2020/01/30/business/juul-altria-vaping.html
AMCR	Amcor	incomplete data set / data not fully available / data quality issue	
AEE	Ameren	December, 2nd 2019: Change in CEO / chairman / board members	https://d18rn0p25nwr6d.cloudfront.net/CIK-0001002910/f2fcf79f-8800-4686-9667-2e355d7eabec.pdf
AMT	American Tower	March, 16th 2020: Change in CEO / chairman / board members	https://americantower.gcs-web.com/static-files/3d099333-4c50-4147-b3f5-cbe84c6099d9
AWK	American Water Works	November, 22 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.globest.com/2019/11/22/american-water-works-to-sell-ny-regulated-operations-in-608m-deal/

AON	Aon	March, 9th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.artemis.bm/news/aon-willis-towers-watson-to-merge/
APTV	Aptiv	insufficient data quality / availability	
ACGL	Arch Capital Group	January, 27th., 2020: Change in CEO / chairman / board members	https://www.reinsurancene.ws/arch-promotes-prashant-nema-to-chief-information-officer/
AJG	Arthur J. Gallagher & Co.	March 16th, 2020: Change in CEO / chairman / board members	https://www.reinsurancene.ws/arthur-j-gallagher-adds-christopher-miskel-to-board/
T	AT&T	April 24th, 2020: Change in CEO / chairman / board members	https://about.att.com/story/2020/att_ceo.html
ATO	Atmos Energy	incomplete data set / data not fully available / data quality issue	
BAX	Baxter International	December, 2nd, 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.medtechdive.com/news/baxter-closes-350m-acquisition-of-sanofis-seprafilm-adhesion-barrier/568238/
BDX	Becton Dickinson	November,25 2019: Change in CEO / chairman / board members	https://www.hrkatha.com/people/movement/becton-dickinson-appoints-anant-garg-as-chro/
BBY	Best Buy	February, 4th 2019: Best Buy decides to keep its CEO following misconduct investigation	https://www.cnn.com/2020/02/04/business/best-buy-ceo-investigation-ends/index.html
BLK	BlackRock	incomplete data set / data not fully available / data quality issue	
BA	Boeing	December, 23 2019: Change in CEO / chairman / board members	https://www.cnn.com/2019/12/23/business/boeing-dennis-muilenburg/index.html
BWA	BorgWarner	January, 28th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.forbes.com/sites/greggardner/2020/01/28/borgwarner-to-buy-delphi-technologies-in-33-billion-deal/
BSX	Boston Scientific	incomplete data set / data not fully available / data quality issue	

AVGO	Broadcom Inc.	January, 8th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.techzine.eu/news/security/44358/broadcom-sells-part-of-symantec-to-accenture/
CHRW	C.H. Robinson	February, 12th 2020: Lawsuit / compliance issue	https://landline.media/farmers-seek-class-action-status-in-1-1-billion-lawsuit-against-c-h-robinson/
CPT	Camden Property Trust	incomplete data set / data not fully available / data quality issue	
CAH	Cardinal Health	March, 19th 2020: Change in CEO / chairman / board members	https://www.prnewswire.com/news-releases/cardinal-health-names-jason-hollar-as-new-chief-financial-officer-301026480.html
CARR	Carrier Global	incomplete data set / data not fully available / data quality issue	
CTLT	Catalent	April, 29th, 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.catalent.com/catalent-news/catalent-signs-agreement-with-johnson-johnson-for-lead-covid-19-vaccine-candidate/
CNP	CenterPoint Energy	February, 20th 2020: Change in CEO / chairman / board members	https://www.courierpress.com/story/news/2020/02/20/ceo-centerpoint-energy-buyer-evansvilles-vectren-steps-down/4818806002/
CRL	Charles River Laboratories	December, 16th 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.genengnews.com/news/charles-river-labs-to-acquire-hemacare-for-380m-expanding-presence-in-cell-therapy/
SCHW	Charles Schwab Corporation	November, 25th 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.cnn.com/2019/11/25/investing/charles-schwab-td-ameritrade/index.html
CMG	Chipotle Mexican Grill	March, 6th 2020: Change in CEO / chairman / board members	https://www.nrn.com/fast-casual/steve-ells-company-founder-steps-down-executive-board-chairman-chipotle-mexican-grill
CMS	CMS Energy	incomplete data set / data not fully available / data quality issue	
CTSH	Cognizant	February, 3rd 2020: Major merger, acquisition, partnership or sale of sub-company	https://news.cognizant.com/2020-02-03-Cognizant-Acquires-Code-Zero-a-Leading-Consultancy-for-Cloud-Based-Configure-Price-Quote-and-Billing-Solutions
CSGP	CoStar Group	March, 9th 2020: Change in CEO / chairman / board members	https://www.mpamag.com/us/specialty/commercial/costar-group-promotes-two-high-ranking-female-executives/216286

DHR	Danaher Corporation	March 31st 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.bioprocessintl.com/deal-making/cytiva-rises-out-of-ge-healthcare-as-danaher-completes-21bn-deal
DVA	DaVita Inc.	December, 18th 2019: Change in CEO / chairman / board members	https://www.prnewswire.com/news-releases/davita-kidney-care-names-new-chief-medical-officer-300976586.html
DLR	Digital Realty	March, 13th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.fierce-network.com/telecom/digital-realty-closes-8-4-billion-deal-to-buy-interxion
DD	DuPont	incomplete data set / data not fully available / data quality issue	
EBAY	eBay	incomplete data set / data not fully available / data quality issue	
LLY	Eli Lilly and Company	January, 14th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.pharmazeutische-zeitung.de/pharmakonzern-eli-lilly-kauft-biotec-firma-dermira-115045/
EQT	EQT	incomplete data set / data not fully available / data quality issue	
EQIX	Equinix	incomplete data set / data not fully available / data quality issue	
EL	Estée Lauder Companies (The)	incomplete data set / data not fully available / data quality issue	
ES	Eversource	February, 26th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.masslive.com/news/2020/02/eversource-to-buy-columbia-gas-for-11b-expects-to-work-with-regulators-and-consumer-groups-over-30-days.html
EXC	Exelon	December, 10th 2019: Change in CEO / chairman / board members	https://www.blackengineer.com/news/calvin-g-butler-is-new-svp-of-exelon-and-ceo-of-exelon-utilities/
EXPE	Expedia Group	Arpil, 23th 2020: Change in CEO / chairman / board members	https://www.fvw.de/counter/karriere/reiseportal-expedia-ernennt-neuen-ceo-und-sichert-sich-milliarden-208335
FFIV	F5, Inc.	incomplete data set / data not fully available / data quality issue	

FRT	Federal Realty	incomplete data set / data not fully available / data quality issue	
FOXA	Fox Corporation (Class A)	March, 18th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.macrumors.com/2020/03/18/fox-corp-buys-tubi-streaming-platform/
GL	Globe Life	incomplete data set / data not fully available / data quality issue	
HIG	Hartford (The)	incomplete data set / data not fully available / data quality issue	
PEAK	Healthpeak	incomplete data set / data not fully available / data quality issue	
HOLX	Hologic	November, 20th 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.massdevice.com/hologic-to-sell-cynosure-medical-aesthetics-business-for-205m/
HST	Host Hotels & Resorts	December, 12th 2019: Change in CEO / chairman / board members	https://hotelbusiness.com/host-hotels-resorts-cfo-to-step-down/
HWM	Howmet Aerospace	incomplete data set / data not fully available / data quality issue	
IBM	IBM	January, 31st 2020: Change in CEO / chairman / board members	https://www.reuters.com/article/business/ibms-surprise-ceo-arvind-krishna-to-take-over-from-ginni-rometty-idUSKBN1ZU2LV/
INTC	Intel	incomplete data set / data not fully available / data quality issue	
IPG	Interpublic Group of Companies (The)	incomplete data set / data not fully available / data quality issue	
INTU	Intuit	Feburary, 24th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.ft.com/content/d9230f22-5748-11ea-abe5-8e03987b7b20
IQV	IQVIA	incomplete data set / data not fully available / data quality issue	

IRM	Iron Mountain	incomplete data set / data not fully available / data quality issue	
JNPR	Juniper Networks	November, 27th, 2019: Change in CEO / chairman / board members	https://www.lightreading.com/optical-networking/koley-quits-as-juniper-s-cto
KEY	KeyCorp	incomplete data set / data not fully available / data quality issue	
KEYS	Keysight	incomplete data set / data not fully available / data quality issue	
KMB	Kimberly-Clark	incomplete data set / data not fully available / data quality issue	
KHC	Kraft Heinz	November, 14th 2019: Change in CEO / chairman / board members	https://www.forbes.com/sites/martingiles/2019/11/14/kraft-heinz-cio-uses-ai-machine-learning/
LDOS	Leidos	incomplete data set / data not fully available / data quality issue	
LMT	Lockheed Martin	March, 17th 2020: Change in CEO / chairman / board members	https://satelliteprome.com/news/lockheed-martin-appoints-james-d-taiclet-as-president-and-ceo/
MPC	Marathon Petroleum	March, 19th 2020: Change in CEO / chairman / board members	https://www.rigzone.com/news/hennigan_succeeds_heminger_at_marathon_petroleum-19-mar-2020-161438-article/
MKTX	MarketAxess	November, 06th 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.thetradenews.com/marketaxess-completes-150-million-liquidityedge-acquisition/
MAS	Masco	incomplete data set / data not fully available / data quality issue	
MA	Mastercard	February, 25th 2020: Change in CEO / chairman / board members	https://www.mastercard.com/news/europe/de-de/newsroom/pressemitteilungen/de-de/2020/februar/michael-miebach-wird-ceo-von-mastercard/
MTCH	Match Group	January, 28th 2020: Change in CEO / chairman / board members	https://www.prnewswire.com/news-releases/match-group-names-sharmistha-dubey-chief-executive-officer-300994817.html
MRK	Merck & Co.	March 2020: Regulatory relief on Libor/benchmark reforms - FASB guidance, accounting impact	https://www.sec.gov/Archives/edgar/data/310158/000031015820000009/mrk0331202010q.htm

META	Meta Platforms	incomplete data set / data not fully available / data quality issue	
MET	MetLife	incomplete data set / data not fully available / data quality issue	
MGM	MGM Resorts	January, 14th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.latimes.com/business/story/2020-01-14/mgm-grand-mandalay-bay-sale
MU	Micron Technology	incomplete data set / data not fully available / data quality issue	
MHK	Mohawk Industries	incomplete data set / data not fully available / data quality issue	
MCO	Moody's Corporation	January, 23th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.businesswire.com/news/home/20200123005214/en/Moody%E2%80%99s-Acquires-RDC-a-Leader-in-Risk-and-Compliance-Intelligence-Data-and-Software
MS	Morgan Stanley	February, 20th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.pbs.org/newshour/economy/morgan-stanley-to-buy-e-trade-for-13-billion
NWL	Newell Brands	March, 3rd 2020: Lawsuit / compliance issue	https://www.wsj.com/articles/newell-brands-is-investigated-by-sec-11583275613
NI	NiSource	February, 28th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.utilitydive.com/news/nisource-sells-off-controversial-massachusetts-columbia-gas-assets-for-11/573148/
NXPI	NXP Semiconductors	March, 6th 2020: Change in CEO / chairman / board members	https://www.electronicsweekly.com/news/business/seivers-succeed-clemmer-nxp-ceo-2020-03/
OXY	Occidental Petroleum	April, 3rd 2020: Change in CEO / chairman / board members	https://www.reuters.com/article/business/occidental-names-new-cfo-in-latest-management-change-idUSKBN21L37V/
ODFL	Old Dominion	incomplete data set / data not fully available / data quality issue	
OMC	Omnicom Group	incomplete data set / data not fully available / data quality issue	

ORCL	Oracle Corporation	December, 16th 2019: Change in CEO / chairman / board members	https://www.datacenterdynamics.com/en/news/safra-catz-named-sole-oracle-ceo-under-larry-ellison/
OGN	Organon & Co.	incomplete data set / data not fully available / data quality issue	
PYPL	PayPal	November, 20th 2019: Major merger, acquisition, partnership or sale of sub-company	https://newsroom.paypal-corp.com/2019-11-20-PayPal-to-Acquire-Honey
PEP	PepsiCo	March, 11th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.prnewswire.com/news-releases/pepsico-to-acquire-rockstar-expanding-presence-in-fast-growing-energy-category-301021412.html
PSX	Phillips 66	incomplete data set / data not fully available / data quality issue	
PPL	PPL Corporation	February, 26th 2020: Change in CEO / chairman / board members	https://www.prnewswire.com/news-releases/ppl-chief-executive-officer-to-retire-june-1-sorgi-named-successor-301011720.html
PLD	Prologis	incomplete data set / data not fully available / data quality issue	
QRVO	Qorvo	incomplete data set / data not fully available / data quality issue	
RF	Regions Financial Corporation	incomplete data set / data not fully available / data quality issue	
ROK	Rockwell Automation	incomplete data set / data not fully available / data quality issue	
RCL	Royal Caribbean Group	February, 7th 2020: Major merger, acquisition, partnership or sale of sub-company	https://skift.com/2020/02/07/tui-and-royal-caribbean-expand-cruise-partnership-with-1-3-billion-deal/
SPGI	S&P Global	incomplete data set / data not fully available / data quality issue	
CRM	Salesforce	February, 26th 2020: Change in CEO / chairman / board members	https://www.celonis.com/press/business-insider-the-head-of-salesforce-s-international-business-is-joining-hot-ai-startup-celonis-amid-a-bigger-shakeup-at-the-cloud-software-giant/

SLB	Schlumberger	incomplete data set / data not fully available / data quality issue	
NOW	ServiceNow	incomplete data set / data not fully available / data quality issue	
SPG	Simon Property Group	Feburary, 11th 2020: Major merger, acquisition, partnership or sale of sub-company	https://commercialobserver.com/2020/02/simon-property-rival-taubman-3-6b-retail-sales-malls/
SJM	J.M. Smucker Company (The)	November, 14th 2019: Change in CEO / chairman / board members	https://www.foodbusinessnews.net/articles/14894-jm-smucker-co-shakes-up-leadership-structure
SEDG	SolarEdge	incomplete data set / data not fully available / data quality issue	
SWK	Stanley Black & Decker	incomplete data set / data not fully available / data quality issue	
STT	State Street Corporation	March, 3rd 2020: Change in CEO / chairman / board members	https://financialit.net/news/people-moves/state-street-global-advisors-announces-appointment-kim-hochfeld-global-head-cash
SNPS	Synopsys	incomplete data set / data not fully available / data quality issue	
SYY	Sysco	March, 4th 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.bloomberg.com/news/articles/2020-03-03/sysco-is-said-to-approach-germany-s-metro-on-potential-takeover
TMUS	T-Mobile US	April, 1st 2020: Major merger, acquisition, partnership or sale of sub-company	https://www.npr.org/2020/04/01/825523250/t-mobile-completes-takeover-of-rival-company-sprint
TROW	T. Rowe Price	insufficient data quality / availability	
TPR	Tapestry, Inc.	February, 6th, 2020: Change in CEO / chairman / board members	https://fashionunited.nz/news/people/tapestry-announces-key-leadership-appointments/2020020610927
TSLA	Tesla, Inc.	insufficient data quality / availability	
TSCO	Tractor Supply	February, 6th 2020: Change in CEO / chairman / board members	https://www.nashvillepost.com/new-tractor-supply-ceo-promotes-three-to-c-suite/article_cf1cc427-1125-5f95-a448-605dcfd461d9.html

UDR	UDR, Inc.	insufficient data quality / availability	
UAL	United Airlines Holdings	December, 5th, 2019: Change in CEO / chairman / board members	https://www.prnewswire.com/news-releases/united-airlines-announces-leadership-transition-300969566.html
UNH	UnitedHealth Group	insufficient data quality / availability	
UHS	Universal Health Services	insufficient data quality / availability	
VTRS	Viatris	November, 13th. 2019: Major merger, acquisition, partnership or sale of sub-company	https://www.businesstoday.in/latest/corporate/story/mylan-nv-pfizer-say-the-combined-entity-will-be-called-viatris-239226-2019-11-13
V	Visa Inc.	January, 13th 2020: Major merger, acquisition, partnership or sale of sub-company	https://techcrunch.com/2020/01/13/visa-is-acquiring-plaid-for-5-3-billion-2x-its-final-private-valuation/
WBA	Walgreens Boots Alliance	December, 12 20 Major merger, acquisition, partnership or sale of sub-company	https://www.businesswire.com/news/home/20191212005230/en/Walgreens-Boots-Alliance-and-McKesson-to-Create-German-Wholesale-Joint-Venture
WEC	WEC Energy Group	insufficient data quality / availability	
WFC	Wells Fargo	February, 21th 2020: Lawsuit / compliance issue	https://www.washingtonpost.com/business/2020/02/21/wells-fargo-fake-accounts-settlement/
WDC	Western Digital	insufficient data quality / availability	
WHR	Whirlpool Corporation	January, 8th 2020: Lawsuit / compliance issue	https://www.theguardian.com/business/2020/jan/09/whirlpool-refund-uk-customers-fire-risk-washing-machines-which
WTW	Willis Towers Watson	March, 6th 2020: Major merger, acquisition, partnership or sale of sub-company	https://aon.mediaroom.com/2020-03-09-Aon-to-Combine-with-Willis-Towers-Watson-To-Accelerate-Innovation-on-Behalf-of-Clients
XEL	Xcel Energy	insufficient data quality / availability	