Sentiment of S&P 500 companies' earnings conference calls during COVID-19 and its effect on stock performance

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ABSTRACT,
The COVID-19 pandemic sparked a global crisis and introduced unprecedented uncertainty into the global markets. This research investigates the dynamics of sentiment expressed in earnings conference calls of S&P 500 companies during the COVID-19 pandemic and how it relates to stock performance. The importance of textual data in investor communication during extreme conditions is explored by focusing on three areas: differences in sentiment across the 11 S&P 500 sectors, sentiment changes over time and textual sentiment as a predictor of stock returns. A sentiment score was created using the Loughran-McDonald financial dictionary, extracting sentiment data from both the presentation and Q&A sections of earnings call transcripts from 2019 to 2023. Monthly stock returns were calculated and integrated with sentiment data of the S&P 500 and its sectors. Moreover, statistical tests were performed to examine sectoral sentiment variations, differences in sentiment between time periods and a correlation between sentiment and stock performance. Results show significant sectoral differences, with financials, real estate, utilities and materials expressing more negative sentiment during the pandemic. Sentiment also dropped sharply in the early phase of the pandemic (2020), but recovered and stabilized rapidly thereafter. However, no significant correlation was found between sentiment and next month's return. These findings suggest that while earnings call sentiment reflects patterns across sectors and time, it does not provide a reliable predictive power for returns on a monthly basis. Nevertheless, this research presents opportunities for future research, including investigation of immediate returns and the potential of detecting irrational behavior during distress.

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Keywords
Textual analysis, Earnings conference calls, COVID-19, S&P 500, Stock performance, Sentiment dynamics

During the preparation of this work, the author used Grammarly in order to check grammar and spelling, and ChatGPT for idea generation. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

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1. INTRODUCTION

In 2020, the COVID-19 pandemic profoundly impacted global economies, resulting in widespread disruptions to daily life and business operations, including government-imposed lockdowns, shifts in consumer behavior and challenges regarding the labor market (Sevgili et al., 2025). Following these disruptions, the global stock markets experienced big shifts, and sectors like travel and hospitality suffered, while the pharmaceutical industry thrived (Jones et al., 2021). This shock to the financial markets is also outlined by Zhang et al. (2020), who identified substantial increases in volatility in the global markets due to the pandemic. A study by Albulescu (2021) highlighted that the uncertainty related to the COVID-19 crisis amplified the volatility seen in U.S. financial markets.

The amplification of volatility in the financial markets created an unprecedented level of risk, which caused panic among investors of publicly traded companies (Zhang et al., 2020). "Predicting financial risks of publicly traded companies is of great interest to capital market participants." (Yu & Yang, 2019). In the article by Yu and Yang (2019), the importance of financial risk to investors is emphasized. Investors will measure financial risks through traditional quantitative methods like the analysis of data found in financial statements. However, more qualitative methods are increasingly incorporated by stock market investors. Textual analysis is one such emerging qualitative method that allows investors to retrieve valuable information from reports and other data disclosed by publicly listed companies that cannot be revealed through financial statements. For instance, textual data published by companies like investor meetings and earnings conference calls contains language that "have been shown to be correlated with future stock returns, earnings, and even future fraudulent activities of management." (Loughran & Mcdonald, 2016).

Earnings conference calls are meetings with relevant stakeholders, like investors, where the executives report their operational outcomes, financial performance and future outlook. This is followed by a session where stakeholders can ask the management of the company questions. Afterwards, the transcripts of these calls are published, generally every quarter (Wang & Hua, 2014). Various studies used the text transcripts of earnings conference calls and applied textual analysis to identify risk, exposure and sentiment and explore different firm characteristics. Earnings conference call transcripts were used to measure firm-level risk and exposure and explore their effects on companies (Hassan et al., 2023; Hassan et al., 2019; Sautner et al., 2023). In other studies, sentiment and speech analysis were performed to identify the predictive value of emotional tone and attitude on financial risk and performance (Alta'any et al., 2025; Hajek & Munk, 2023; Price et al., 2012; Yu & Yang, 2019). Additionally, Loughran and McDonald (2011, 2016) made contributions to textual analysis, such as word lists that better identify sentiment in financial texts.

Previous studies analyzed sentiment in earnings conference calls and its impact on firm characteristics (Alta'any et al., 2025; Hajek & Munk, 2023; Price et al., 2012; Yu & Yang, 2019). However, these studies did not address specific contexts or time frames, like the COVID-19 pandemic, which resulted in an economic downturn that posed unique challenges and uncertainties to financial markets and companies (Goodell, 2020). Therefore, this research aims to bridge this gap by generating novel insights on the value of sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic.

1.1 Research Objective and Question

The objective of this research is to conduct an analysis of the sentiment expressed in earnings conference calls of S&P 500 companies during the COVID-19 pandemic. The aim is to investigate how the sentiment conveyed by company executives during earnings conference calls predicts stock performance. Additional insights will be provided through analysis of sectoral differences and changes over time.

A research question formulated for this research is:

- "How does the sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic correlate with their stock performance?"

Three relevant sub-questions are:

- "How does the sentiment in earnings conference calls vary across different sectors within the S&P 500 during the pandemic?"
- "How does the sentiment in earnings conference calls of S&P 500 companies change before, during and after the pandemic?"
- "How does the sentiment in earnings conference calls affect the stock performance of S&P 500 companies during the pandemic?"

1.2 Academic and Practical Relevance

This research holds academic relevance as it addresses a gap in the current literature by focusing on the sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic. It extends the knowledge of the beneficial use of textual sources published by publicly listed companies to explore different firm characteristics. As mentioned by Yu and Yang (2019), research in finance and computational linguistics increasingly uses textual sources of companies, including transcripts of earnings conference calls, to perform textual analysis to study various topics. This research was inspired by this emerging method of analysis and intends to focus on exploring stock performance using the sentiment found in earnings conference call transcripts, thereby delivering a novel contribution to existing literature.

This research is practically relevant as it has the potential to provide valuable insights for stakeholders, including investors, financial analysts and executives. The linguistic tone of earnings conference calls is a significant predictor of stock returns and trading volume. Also, information contained in the sentiment of earnings call wording can be informative of the market's reaction (Price et al., 2012). Thus, examining and understanding the relationship between sentiment in earnings conference call transcripts of S&P 500 companies and their stock performance during economic downturns, specifically the COVID-19 pandemic, can help investors to make better-informed decisions.

Especially since the pandemic led to an unstable and unpredictable economic environment by disrupting firm's operations and, as a result, made it challenging to forecast a firm's performance in the near future, knowledge about the usefulness of textual sources published by publicly listed companies, besides quantitative data like financial statements, can be valuable to investors (Maslar et al., 2021). Financial analysts can benefit from this knowledge, for instance, by enhancing their forecasts of stock performance based on textual data from earnings calls. Also, executives can use this information to get a better understanding of how the words and attitudes they use during earnings conference calls influence investor behavior and confidence, as well as their company's valuation.

2. LITERATURE REVIEW

In this section, a literature review is conducted to provide an overview of the existing research and theoretical frameworks that are relevant to the objective and key variables of this research. Literature on sentiment in earnings conference calls and its relation to firm performance will be reviewed. In addition, the Efficient Market Hypothesis (EMH) and behavioral finance will be discussed to gain an understanding of stock market price behavior. To conclude, the sectoral differences and temporal changes in stock performances during COVID-19 will be examined.

2.1 Sentiment in Earnings Conference Calls

Quarterly earnings conference calls have gained interest from investors and researchers as it is an important source of information. It can be used in understanding the role that sentiment in the financial disclosures of companies plays in being an indicator of stock performance (Barahona Diaz & Hu, 2024). Research found that executives' emotional tones and attitudes, both textually and vocally, have an impact on future firm performance, including profitability and returns (Hassan et al., 2023; Mayew & Venkatachalam, 2012). Additionally, Tetlock et al. (2008) suggests that linguistic media content, like earnings call transcripts, captures qualitative insights such as sentiment about a company that would not be revealed by traditional financial metrics. Investors are then quick to incorporate these insights into stock prices. Though, in order to capture this information, the art of textual analysis has to be understood since textual analysis is substantially less precise compared to traditional quantitative methods (Loughran & Mcdonald, 2016). Blau et al. (2015) also adds to this by mentioning that the tone in earnings conference calls can be subtle, context-specific and difficult to interpret.

However, using sentiment data from textual sources can be misleading. Huang et al. (2014) found evidence that managers can manage their tone strategically to mislead investors about firm fundamentals. This was contradicted by Fu et al. (2021) who argued that managers engage in truthful communication by investigating the role of optimistic call tone in predicting stock price crash risk. It was stated that monitoring from the environment, for example by analysts, made honest communication more pronounced.

Analysts are important for executives since the sentiment in the earnings conference call can determine analysts' follow-up behavior, like stock ratings (Chen et al., 2023). Engagement with analysts is also shown to be positively associated with stock returns (Rennekamp et al., 2022), emphasizing their important role. The tone of conference calls, especially from the question and answer section, explains abnormal returns from earnings announcements (Doran et al., 2012). Yet, the tone of managers does not only reflect the manager's information about future company performance or strategy. It also reflects manager-specific traits, like a natural tendency toward optimism or pessimism. Therefore, interpretations of the tone in earnings conference calls should account for personal biases (Davis et al., 2015).

2.2 Efficient Market Hypothesis and Behavioral Finance

Many theories exist around stock market price behavior. A well-known theory is the Efficient Market Hypothesis (EMH), which states that capital markets are efficient when all available information is reflected in the share price, leaving no opportunities for abnormal profits based on this available information (Fama, 1965, 1970). It is found that investors' stock returns are often random and that they are not capable of consistently generating excess returns, thereby providing support for the EMH. On the other hand, "EMH fails to explain excess volatility in stock prices, investor overreaction, seasonality in returns, asset bubbles, etc." (Degutis & Novickytė, 2014). Another study, by Borges (2010), tested the EMH in European markets, which led to mixed evidence of it.

Since the acceptance of the EMH, criticism has appeared about the general belief that markets are efficient and incorporate information into stock prices immediately, leaving no opportunity to earn above-average returns (Malkiel, 2003). This criticism led to the popularization of behavioral finance, a field of study that emerged due to the inability of traditional models to fully explain market movements. Behavioral finance focuses on the influence of human psychology on financial decisions and market behavior, and has led to the realization that emotions, biases and irrational behavior play a role in stock price fluctuations, leading to the integration of psychological factors (Shiller, 2003).

Vasileiou et al. (2021) conducted a study finding support for the explanatory power of behavioral finance on prices of the stock market, more specifically the S&P 500, during COVID-19. It concluded that, when extreme conditions occur, behavioral factors, such as fear, may be indicators of investor decisions. In addition, it was discovered that the health risk associated with COVID-19 was underestimated, contrasting the view of the EMH that all available information is always incorporated in the stock market prices. However, Stracca (2004) argues that, although incorporating psychological ideas has enriched the field of finance by offering a more comprehensive understanding of investor behavior, behavioral finance runs the risk of becoming too complex. It is also stated that there is no conclusive evidence to prove that the irrationality in the financial markets, which can be explained by behavioral finance, allows investors to outperform the market, although indications are suggesting that the market may not always be rational.

2.3 Stock Performance during COVID-19

The impact of COVID-19 exposure on stock market returns was analyzed by Hassan et al. (2023). In the study, it was found that when the exposure is separated into risk and sentiment components, the negative sentiment about COVID-19 is the prevalent factor explaining returns. This suggests that investor perceptions and emotions may be a driver of stock market movements during extreme economic conditions, like those caused by the pandemic (Mishra et al., 2020). Furthermore, Costola et al. (2023) had similar findings showing a statistically significant and positive relationship between COVID-19 sentiments and the S&P 500, highlighting that news on the pandemic impacted expectations of market participants. Dissecting the sentiment into positive, negative and neutral sentiment showed that a decline in negative news had a statistically significant impact on financial returns, indicating that stocks tended to perform better when there was a reduced negative sentiment. These findings show the relevance of COVID-19 when it comes to stock performance.

2.3.1 Sectoral Differences

The COVID-19 pandemic triggered a U.S. stock market crash; however, not all sectors reacted equally to the crisis. Sectors, such as healthcare, food, natural gas and software, exhibited abnormally strong stock performance. Meanwhile, industries that were heavily impacted by pandemic-related consequences included the crude petroleum, real estate, entertainment and hospitality sectors, losing more than 70% of their market capitalizations (Mazur et al., 2021). Performance of the 11 S&P sectors was illustrated by Matos et al. (2021), showing varying reactions to the pandemic. In the first and second quarters of 2020, financials, utilities, industrials, real estate and energy were among the worst-performing sectors. In contrast, relative strength was demonstrated by information technology, consumer discretionary and health care, which remained relatively stable.

Changes in sentiment across sectors were also identified in the first months of 2020. A substantial negative change in executive sentiment was illustrated for companies in the financials, industrials and energy sectors. However, this negative change was only seen in companies based in the Asia-Pacific (APAC) region and companies mentioning COVID-19 in their earnings conference calls (Chan & Joseph, 2020).

The effect of the COVID-19 pandemic differed between developed and emerging countries as well. Stock markets in emerging countries experienced a significantly greater negative impact than in the developed countries, especially for firms with small market capitalizations and growth stocks. There are also differences in the sectors that are impacted between emerging and developed countries. While in emerging countries, healthcare and telecommunications experienced positive impacts during the crisis, the information technology sector benefited in developed countries (Harjoto & Rossi, 2023).

2.3.2 Temporal Changes

Global markets did not actively react at the early stage of the COVID-19 pandemic (Prajwal et al., 2021). Once markets responded to the speculation, rumors and negative news, a dramatic drop in stock prices occurred (Valle-Cruz et al., 2022). Nevertheless, over the first year of the pandemic, the heightened uncertainty began to decline, with the second wave of the pandemic having a less drastic effect than the first wave (Keliuotyte-Staniuleniene & Kviklis, 2022). However, due to periods of severe market turbulence increasing investor attention (Jiang et al., 2021) and sentiment playing a role in stock performance (Costola et al., 2023; Hassan et al., 2023), markets saw significant volatility throughout the pandemic. Bai et al. (2023) conducted a study where it was found that positive sentiment helped to increase stock market returns, even during the worst periods of the pandemic. Still, negative sentiment had a more significant impact on returns than positive sentiment. Buchheim et al. (2022) identified that, aside from market sentiment, a firm's sentiment can also have an impact on its stock performance. Optimism or pessimism regarding COVID-19 shutdowns influenced the business outlook and behavior, shaping how firms responded to the crisis and ultimately investor perception about the company's stability and potential, impacting stock performance.

2.4 Hypotheses

Based on the literature review, hypotheses are formulated relevant to examining the relationship between sentiment in earnings conference calls and stock performance during the COVID-19 pandemic.

The pandemic affected various sectors differently from others and, consequently, caused variations in stock performances across different sectors (Mazur et al., 2021). Financials, industrials and energy were among the worst-performing sectors of the S&P 500 (Matos et al., 2021). Meanwhile, financials, industrials and energy also saw negative changes in executive sentiment (Chan & Joseph, 2020). Therefore, the following has been hypothesized:

Hypothesis 1: Companies in the financials, industrials and energy sectors express substantially more negative sentiment.

In previous research, it was shown that sentiment, particularly negative sentiment, can be significantly and positively correlated with stock market returns (Bai et al., 2023; Costola et al., 2023; Hassan et al., 2023). Also, managerial sentiment regarding COVID-19 is observed to ultimately influence investor decisions. Furthermore, Vasileiou et al. (2021) indicated that, during extreme conditions, sentiment can have an influence on investor decisions. This leads to the following hypothesis:

Hypothesis 2: Sentiment in earnings conference calls significantly differs between the pre-pandemic, pandemic and post-pandemic periods.

Although comments are made on the use of sentiment expressed in textual sources (Blau et al., 2015; Davis et al., 2015; Huang et al., 2014; Loughran & Mcdonald, 2016), multiple studies argue in favor of sentiment being an explanatory factor of stock performance (Doran et al., 2012; Hassan et al., 2023; Mayew & Venkatachalam, 2012; Tetlock et al., 2008). Also, despite both the EMH and behavioral finance having conflicting ideas, the implementation of psychological factors, like sentiment, in stock market price behavior has reasonable credibility. This leads to the following hypothesis:

Hypothesis 3: Sentiment in earnings conference calls is positively correlated with stock performance.

3. METHODOLOGY

The following sections outline the approach to investigating the effect of sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic on stock performance. The overall research structure is explained, followed by a description of how data is collected. To conclude, the methods of analysis to materialize results are explicated.

3.1 Research Design

The research objective is to perform an investigation into the sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic, focusing on the change in sentiment over the pandemic, sectoral differences and stock performance impact. Analysis will be done of earnings call transcripts from each quarter for the years 2019, 2020, 2021, 2022 and 2023. This will allow for an understanding of shifts and differences of the sentiment expressed pre-pandemic, during the pandemic and post-pandemic.

Sentiment variation will be explored for all companies of the S&P 500 combined. For analysis of sectoral differences, the 11 sectors within the S&P 500, as defined by S&P Global, will be utilized for sectoral grouping (S&P Dow Jones Indices, 2025). The sentiment of companies in the S&P 500 is constructed by taking the sentiment of the earnings call transcripts of the individual companies and using the average sentiment for analysis. For sector analysis, the average sentiment will be taken from the companies within each sector.

Examination of stock performance within the S&P 500 index will be conducted by calculating monthly stock returns. The relationship between sentiment and stock performance is evaluated by examining next month's return and the average monthly sentiment in the month before. In other words, it will be investigated if the average sentiment of month t predicts the return of month t+1.

3.2 Data Collection

Data for this research is collected from earnings conference call transcripts and stock market data of S&P 500 companies. To perform the sentiment analysis, the transcripts of earnings conference calls, which are publicly available, are obtained for the relevant periods using Refinitiv Eikon. These transcripts are the basis for evaluating the sentiment of S&P 500 companies by use of textual analysis.

To measure stock performance, historical price data of the S&P 500 index is retrieved from S&P Dow Jones Indices (2025). This price data allows for the calculation of monthly returns for the complete stock market index. For sector analysis, tickers have to be matched with their sectors, which will be done using sector overviews from TradingView (2025).

The collected data will subsequently be processed and analyzed to examine sentiment in the periods before, during and after the pandemic, sectoral differences and stock performance, as outlined in the following section.

3.3 Data Analysis

The data analysis of this research consists of conducting a sentiment analysis, stock return analysis and further statistical exploration using RStudio. In this section, each of the steps required to produce results for this research is elaborated. First, sentiment is measured using the Loughran and McDonald financial dictionary (Loughran & McDonald, 2024) and a measure of tone (Twedt & Rees, 2012). Then, monthly stock returns are calculated with the rate of return formula (Kenton, 2024). Finally, all data is integrated and analyzed in Excel and RStudio to examine patterns across sectors, compare pandemic periods and assess the relationship between sentiment and stock performance.

3.3.1 Sentiment Analysis

To retrieve the sentiment from the earnings conference call transcripts, a financial dictionary (Loughran & McDonald, 2024) will be employed. Loughran and McDonald (2011) have developed word lists for various types of words, like positive and negative words, that are superior at correctly classifying words in financial texts in comparison to other dictionaries. Prior to this study, it was found that the Loughran-McDonald dictionary, tailored to financial language, does exceptionally well compared to general sentiment tools (Li et al., 2020).

Before conducting sentiment analysis, preprocessing of the textual data is essential to obtain accurate and consistent results. First, the Loughran-McDonald Master Dictionary will be imported into Python and converted into lowercase to ensure correct matching of textual data further in the process.

Similarly, a series of preprocessing steps will be applied to the earnings conference call transcripts. First, all text is converted to lowercase to standardize and reduce the number of unique words. Next, numerical values are removed as they do not contribute to the sentiment analysis. Punctuation is also eliminated to avoid interference with the tokenization of words. In addition, stop words, such as "this" and "the", are excluded since they typically do not contain sentiment. Excess whitespace is stripped to enhance the clarity of the text. Additionally, lemmatization is applied to ensure the words in the transcripts match the words occurring in the dictionary. Finally, tokenization of the text is executed to ensure the text is broken down into individual words.

To complete the sentiment analysis, the sentiment has to be measured for the earnings call transcripts. In this study, both the presentation and the Q&A section of the transcript will be analyzed. This will provide insights into what differences exist between both sections, which can be expected due to the presentation section being well-prepared while the Q&A section is less scripted and contains spontaneous sentiment (Meirkulov et al., 2024).

As mentioned by Loughran and McDonald (2015), the tone is often measured by the count of positive and negative words and scaled to the total number of words in the document. This method can be used to identify whether a text is more positive or more negative, and the relative magnitude of the sentiment (Kearney & Liu, 2014). Twedt and Rees (2012) developed a similar method for measuring tone (1), which will be adopted in this research.

$$Sentiment = 100 * \left[\frac{(positive\ words - negative\ words)}{word\ count}\right] \quad (1)$$

3.3.2 Stock Return Analysis

To measure stock performance, the historical stock price data retrieved during the data collection will be exported and organized into Microsoft Excel. In Excel, the monthly returns will be calculated for the S&P 500 index. The calculation of stock returns is carried out using the rate of return formula (2), which measures the gain or loss of a stock over a specific period (Kenton, 2024).

$$Rate\ of\ return = \left[\frac{new\ value - initial\ value}{initial\ value}\right] \times 100 \quad (2)$$

Once the monthly returns are computed, the data will be imported into RStudio as a CSV file together with sentiment scores derived from the textual analysis of earnings conference call transcripts to facilitate further statistical analysis.

3.3.3 Further Analysis

In RStudio, the resulting data are imported and analyzed to examine variations in sentiment between sectors and pandemic periods, and to evaluate the relationship between sentiment and stock performance. At first, descriptive statistics and visualizations will be generated to give insights into trends, averages and variability of sentiment across sectors and over time. Furthermore, correlation analysis will be conducted to explore the relationship between sentiment and monthly returns.

Additionally, statistical and parametric tests like *t*-tests and Analysis of Variance (ANOVA) will be utilized to test, for instance, whether a difference in sentiment before, during and after the pandemic is statistically significant. A prerequisite for this is that the data is normally distributed, which will be tested by the Shapiro-Wilk test. In the case of a not normally distributed dataset, alternative non-parametric tests will be used, like the Mann-Whitney U test or the Kruskal-Wallis test.

The results from these analyses will be interpreted to assess how sentiment in earnings conference calls evolved, how it varied between sectors and whether it had a statistically significant impact on stock performance. Moreover, this research makes theoretical and practical contributions by adding to existing literature of textual analysis in financial contexts, particularly in periods of uncertainty, and providing insights relevant for investors, analysts and managers. Although there are several limitations, including the fact that this method of capturing sentiment from textual sources is one of multiple methods discussed in the literature. Also, it could remain unclear whether the sentiment in earnings conference calls plays a role in itself or is a proxy of other factors like macroeconomic expectations. Nevertheless, it can still be insightful for financial stakeholders to study the utility of textual sources.

4. RESULTS

This section presents the results gathered during the research. The data retrieved during data collection and textual analysis of the earnings conference calls was collected and analyzed in Excel. Furthermore, the sentiment data of the entire S&P 500 and its sectors and monthly returns were exported into RStudio for further statistical analysis. Data was collected for both the presentation and the Q&A section of the earnings calls to explore variations between the two.

4.1 Summary Statistics

Tables 7 and 8 in the appendix show summary statistics of the variables imported into RStudio. The count, mean, median, min, max, range, variance and standard deviation of the variables are given. The statistics display a general overview of sentiment, sentiment per sector and the monthly return over the years 2019 to 2023. The variables in RStudio have already been prepared in Excel into monthly averages of the sentiment; therefore, these summary statistics offer a broad glance at the data that was collected.

The variable 'sentiment' represents the positive minus the negative word count, relative to the size of the text. 'Monthly return' is a variable that shows the difference between the price at the start of the current month and the next month. The other variables are S&P 500 sectors, which consist of the average monthly sentiment of each sector.

Table 7 shows that the mean sentiments are all quite positive, indicating a generally positive outlook presented by the management of S&P 500 companies. Interestingly, variations in sentiment means of sectors can be observed, indicating differences in sentiment performance over the years 2019 to 2023.

Meanwhile, Table 8 shows a more negative-leaning sentiment for the whole S&P 500 and its sectors separately as well. This suggests a more negative tone during analyst questioning in the question and answer sections compared to the well-prepared presentation by management. Also, in the Q&A section, variations in sentiment across sectors can be observed, similar to the presentation section.

4.2 Hypothesis Testing

The variables presented in Tables 7 and 8 will be used to test the hypotheses developed in the literature review. Before using various statistical tests, the correct tests have to be determined. Statistical tests can be parametric when certain assumptions, like a normal distribution, are met. However, when data is not normally distributed, alternative non-parametric tests can substitute for the parametric tests.

The variables were tested using the Shapiro-Wilk test to check if the data is normally distributed. The results from this test, as illustrated in Tables 9 and 10 in the appendix, show that the majority of the data is not normally distributed for both the presentation and the Q&A section, likely due to a skewed distribution caused by outliers from the pandemic. Therefore, non-parametric tests were used, such as the Mann-Whitney U test, Kruskal-Wallis test, Wilcoxon Signed-Rank test and Spearman's rank correlation coefficient.

4.2.1 Sector Analysis

To test the hypothesis whether the financials, industrials and energy sectors express substantially more negative sentiment, a Mann-Whitney U test was used. Using this test, which measures the overall distribution of values, it was tested whether each sector has lower sentiment than all other sectors, for each sector. This resulted in Tables 1 and 2, showing median_target and median_other as an indication of the differences between the specified sector and all other sectors. It also shows the adjusted *p*-value, which is an adjustment to the *p*-value using the Bonferroni correction. This was done since multiple hypotheses increase the chances of a Type I error, which is accounted for by multiplying the *p*-value by the number of tests. Sentiment data of each sector from March 2020 until May 2023 was used, since this was the official period in which the World Health Organization (WHO) declared an official health emergency (Rigby & Satija, 2023).

Table 1 presents that the financials and utilities sectors differed significantly in comparison to the other sectors of the S&P 500. Figure 9 in the appendix highlights the three sectors expected to perform worse compared to the other sectors. It appears that the sentiment of these sectors was among the sectors with the lowest sentiment during the worst moment of the pandemic.

Table 1. Mann-Whitney U test results (presentation).

Sector	W	p_value	Median _Target	Median _Other	p_adj
Communication Services	4,382	0.404	1.769	1.788	1.000
Consumer Discretionary	9,062	1.000	2.149	1.751	1.000
Consumer Staples	6,680	0.814	1.865	1.780	1.000
Energy	3,235	0.007	1.483	1.811	0.080
Financials	3,977	0.000	1.313	1.833	0.002 **
Health Care	6,620	0.787	1.848	1.783	1.000
Industrials	6,241	0.568	1.845	1.780	1.000
Information Technology	7,518	0.988	1.937	1.770	1.000
Materials	4,805	0.810	1.865	1.780	1.000
Real Estate	3,392	0.030	1.673	1.809	0.332
Utilities	3,147	0.005	1.597	1.830	0.050 *

****, ** and * are statistically significant at 0.001, 0.01 and 0.05, respectively.*

Table 2 presents that the financials, materials and real estate sectors express substantially more negative sentiment than other sectors. Additionally, there is a difference between the Q&A and presentation sections regarding which sectors have significantly more negative sentiment during the pandemic. In Figure 10 (appendix), it can be seen that the three sectors hypothesized to have worse sentiment than other sectors have some of the lowest sentiment scores during the lowest point of the pandemic.

Table 2. Mann-Whitney U test results (Q&A).

Sector	W	p_value	Median _Target	Median _Other	p_adj
Communication Services	6,220	1.000	0.397	0.172	1.000
Consumer Discretionary	8,788	1.000	0.508	0.165	1.000
Consumer Staples	7,690	0.995	0.382	0.166	1.000
Energy	3,470	0.023	0.088	0.219	0.256
Financials	4,492	0.003	0.005	0.218	0.038 *
Health Care	5,950	0.379	0.107	0.213	1.000
Industrials	7,044	0.932	0.294	0.177	1.000
Information Technology	7,160	0.954	0.343	0.179	1.000
Materials	2,671	0.001	-0.040	0.218	0.006 **
Real Estate	1,828	0.000	-0.200	0.232	0.000 ***
Utilities	3,746	0.072	0.116	0.214	0.789

****, ** and * are statistically significant at 0.001, 0.01 and 0.05, respectively.*

4.2.2 Time-Series Analysis

To test the second hypothesis regarding whether sentiment is significantly different between pandemic periods, the Kruskal-Wallis test was used with the Wilcoxon signed-rank test as a follow-up for significant Kruskal-Wallis test results. The Kruskal-Wallis test tests whether at least one group is different, whereas the Wilcoxon signed-rank test tests whether the difference between each pair of the groups is significantly different. There are three groups: Pre-COVID, COVID and Post-COVID. These groups contain the sentiment scores from 2019 until February 2020, March 2020 until April 2023 and May 2023 until the end of 2023, respectively. This means the official pandemic period, as declared by the WHO, was used.

The results in Table 3 indicate that neither the presentation nor the Q&A parts showed a statistically significant difference in sentiment scores across the three groups.

Table 3. Kruskal-Wallis test result.

Section	Statistic	df	p_value
Presentation	3.287	2	0.193
Q&A	4.443	2	0.108

Figures 1 and 2 show that the sentiment in both the presentation and Q&A parts experienced a significant drop, although not very long-lasting.

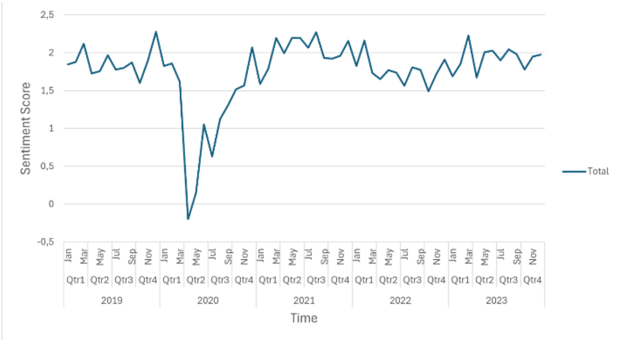

Figure 1. Sentiment 2019 – 2023 (presentation)

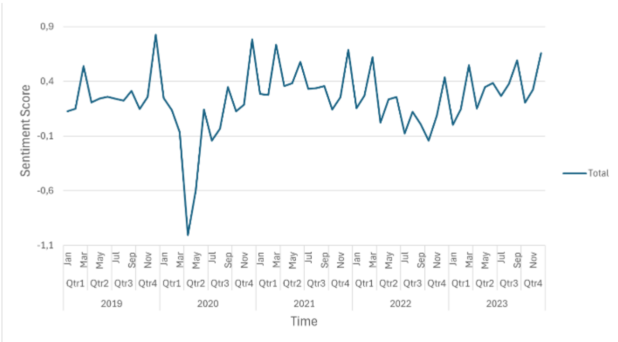

Figure 2. Sentiment 2019 – 2023 (Q&A)

Adjustment of the group COVID to start from March 2020 until the end of 2020 shows different results. Table 4 shows that there is a significant difference between the three groups in the presentation section. The Q&A section indicates similar results, however, not statistically significant ($p < 0.05$).

Table 4. Kruskal-Wallis test results, 2020 only.

Section	Statistic	df	p_value
Presentation	15.129	2	0.001 ***
Q&A	5.905	2	0.052

****, ** and * are statistically significant at 0.001, 0.01 and 0.05, respectively.*

A follow-up Wilcoxon signed-rank test (Table 5) shows that the sentiment in the COVID group during the short-term pandemic period is significantly different from the pre-COVID and post-COVID groups.

Table 5. Wilcoxon signed rank test results, 2020 only (presentation).

Group 1	Group 2	Adjusted *p*-value
COVID	Pre-COVID	0.002 **
Post-COVID	Pre-COVID	1.000
COVID	COVID	
Post-COVID	COVID	0.000 ***

****, ** and * are statistically significant at 0.001, 0.01 and 0.05, respectively.*

4.2.3 *Correlation Analysis*

The third hypothesis was tested using Spearman's rank correlation coefficient. It tests whether sentiment is positively correlated to returns over the WHO-determined pandemic period. To test this, the variable 'sentiment' and the next month's monthly return were tested for a correlation and regression.

Table 6 shows neither of the parts in earnings conference calls indicates a positive relationship between sentiment and next month's monthly return. Moreover, the results are not statistically significant, indicating a weak, negative relationship.

Table 6. Spearman's rank correlation coefficient test results.

Section	Rho..ρ.	*p*.value
Presentation	-0.101	0.552
Q&A	-0.060	0.725

Figures 3 and 4 illustrate this negative and weak relationship. Also, robust regressions, shown in Tables 12 and 13 in the appendix, indicate no significant correlation between sentiment and next month's monthly return.

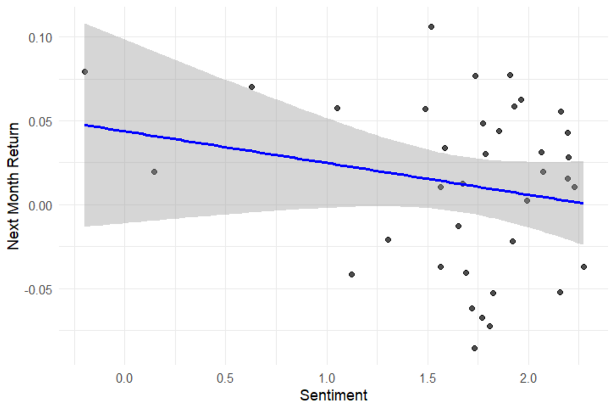

Figure 3. Scatterplot of sentiment vs. next month return (presentation).

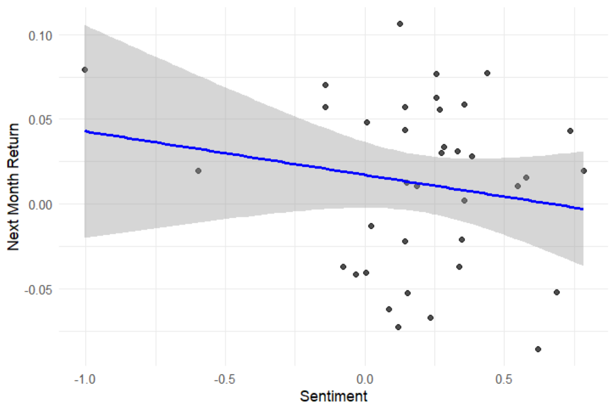

Figure 4. Scatterplot of sentiment vs. next month return (Q&A).

5. DISCUSSION

This chapter discusses the results of this research. The conclusion and answers to the hypotheses and research questions will be presented. Additionally, the theoretical and practical implications of this research are outlined. Finally, the limitations and suggestions for future research are given.

5.1 Conclusion

The undertakings in this research set out to answer the research question: "How does the sentiment in earnings conference calls of S&P 500 companies during the COVID-19 pandemic correlate with their stock performance?". To answer this, three sub-questions were formulated and operationalized through three hypotheses. First, hypothesis 1, which addressed sectoral differences, was tested in the sector analysis. It was found that sectors including financials, utilities, materials and real estate had significantly worse sentiment during the WHO-defined pandemic period, although this was not consistent across both parts of the call transcripts. Notably, the three hypothesized sectors were among the sectors with the lowest sentiment during the height of the pandemic. Conclusively, these results demonstrate that sectors were indeed affected differently.

Second, hypothesis 2 addressed changes in sentiment over time. The WHO-defined pandemic period led to no statistically significant results; however, on a shorter time frame, the difference in pre-, during and post-pandemic sentiment was significant. This shows that sentiment only dropped for a short moment, indicating the distress it caused to both the management of companies and analysts. Yet, the sentiment recovered quickly and remained stable for the rest of the pandemic, suggesting quick adaptation to the new context.

Third, hypothesis 3 addressed the relationship between sentiment and stock performance. The findings were clear, indicating no statistically significant correlation between sentiment and next month's return in both parts of the transcripts. The correlation coefficient was weak and negative, rejecting the hypothesis of a positive relationship, indicating no predictive power of sentiment on monthly return.

In conclusion, this research has revealed that sentiment dynamics display sectoral and temporal shifts and patterns, yet these patterns did not translate into a correlation between sentiment and stock performance on a monthly basis. The results suggest that the tone in earnings conference calls during the pandemic reflected sector-specific challenges and short-term shocks. However, no evidence is found that these influence investor behavior enough to affect the return of the following month.

5.2 Practical Implications

The findings in this research are relevant for multiple financial stakeholders. For instance, investors and analysts may use sentiment data to assess the tone and communication of companies for insightful information, like irrational behavior, or as an addition to assessment by traditional financial metrics. Moreover, the sectoral differences in sentiment could also be used to contextualize risk exposure by industry. However, the results do demonstrate that sentiment should not be relied upon as a predictive trading signal in a volatile market.

Also, corporate executives may benefit, since the results show variations between the presentation and Q&A section of earnings conference calls, highlighting the influence of the nature of conversations on tone. As the Q&A portion of earnings conference calls can be interpreted as more unscripted since the tone is less positive, it can be useful to know that investors and analysts may value genuine and transparent information rather than polished presentations.

5.3 Theoretical Implications

This study contributes to the literature around behavioral finance, textual analysis and sentiment dynamics with a focus on the COVID-19 pandemic and earnings conference call transcripts. It supports the notion that sentiment reflects market conditions and sectoral variations, particularly in a volatile setting like the pandemic. However, the hypothesis that sentiment can directly influence stock returns is not validated in this research, thereby contradicting prior findings suggesting such a correlation, although the time frame studied in this research is inconsistent with other studies.

The finding that a significant correlation between sentiment and stock return is absent aligns with the Efficient Market Hypothesis (EMH), suggesting that sentiment expressed in the transcripts either lacks new, relevant information or is already priced into the market when it becomes available. Thus, this provides partial support for the EMH. Furthermore, the limitations of behavioral finance are pointed out, suggesting that while sentiment in earnings calls may depict emotion and affect perception, it may not consistently move the markets in predictable ways.

5.4 Limitations

This research has several limitations. First, the sentiment score was formed using dictionary-based textual analysis, which may miss context or sarcasm, or fail to account for nuanced language. Second, the sentiment in both sections of the transcripts may be confounded by individual managerial traits, like an inclination toward optimism or pessimism. Third, this research focuses on monthly returns, potentially being too long a time frame to identify specific market reactions and missing very short-term, direct price reactions to information. Prior studies have shown that immediate returns following publication of earnings announcements can be more sensitive to tone, especially in the Q&A section. Lastly, the vocal tone has not been accounted for in this research, potentially leaving out non-verbal sentiment cues.

5.5 Future Research

Future studies can address some of the limitations mentioned. For example, machine learning or a large language model can be applied to aid in the textual analysis of sentiment, collecting a more context-sensitive sentiment from texts compared to the dictionary-based method. Also, combining the textual sentiment with audio sentiment might provide new insights.

Future research could also explore a similar direction as this research, while investigating immediate stock price reactions following earnings calls rather than on a monthly basis, to detect sentiment-driven market reactions more precisely. Future studies could also compare sentiment expressed during COVID-19 in earnings conference calls to other textual sources like analyst reports.

Further, analyzing the effect of different geographical locations outside of solely the S&P 500 might provide interesting insights that vary from the insights identified in this research. Lastly, future research could investigate whether signs of distress in earnings call sentiment reflect irrational investor behavior, such as overreactions in stock markets due to fear, which may present contrarian buying opportunities, in other words, the opportunity to take advantage of inefficient stock markets.

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7. APPENDICES

7.1 Summary Statistics

Table 7. Summary statistics (presentation).

Variable	COUNT	MEAN	MEDIAN	MIN	MAX	RANGE	VARIANCE	STDEV
Sentiment	60	1.758	1.835	-0.199	2.275	2.474	0.199	0.447
Communication Services	42	1.698	1.809	-0.463	3.188	3.651	0.427	0.654
Consumer Discretionary	60	2.128	2.160	-0.137	2.888	3.025	0.300	0.548
Consumer Staples	60	1.924	1.904	0.303	3.054	2.751	0.292	0.540
Energy	41	1.443	1.518	-1.175	2.162	3.336	0.444	0.666
Financials	60	1.432	1.402	-0.968	4.245	5.212	0.642	0.801
Health Care	58	1.964	1.919	0.057	4.929	4.873	0.600	0.775
Industrials	60	1.623	1.786	-0.276	2.753	3.028	0.448	0.669
Information Technology	60	1.876	1.878	0.545	2.697	2.152	0.159	0.399
Materials	40	1.796	1.821	0.014	2.636	2.622	0.256	0.506
Real Estate	40	1.509	1.719	-0.104	2.272	2.376	0.383	0.619
Utilities	41	1.458	1.571	0.002	2.275	2.273	0.240	0.490
Monthly return	60	0.012	0.020	-0.201	0.146	0.346	0.003	0.057

Table 8. Summary statistics (Q&A).

Variable	COUNT	MEAN	MEDIAN	MIN	MAX	RANGE	VARIANCE	STDEV
Sentiment	60	0.239	0.251	-1.004	0.826	1.830	0.087	0.294
Communication Services	42	0.490	0.480	-0.568	1.234	1.802	0.169	0.411
Consumer Discretionary	60	0.485	0.532	-0.663	1.029	1.692	0.104	0.322
Consumer Staples	60	0.432	0.471	-0.637	1.083	1.720	0.109	0.329
Energy	41	0.117	0.146	-1.237	0.702	1.938	0.120	0.346
Financials	60	0.013	-0.042	-1.690	1.635	3.325	0.297	0.545
Health Care	58	0.299	0.175	-0.973	1.717	2.690	0.270	0.520
Industrials	60	0.244	0.285	-1.425	1.094	2.519	0.183	0.428
Information Technology	60	0.287	0.298	-0.509	1.180	1.689	0.110	0.332
Materials	40	-0.048	-0.024	-0.995	0.414	1.409	0.091	0.302
Real Estate	40	-0.164	-0.172	-0.836	0.377	1.212	0.082	0.286
Utilities	41	0.010	0.052	-0.888	0.950	1.838	0.150	0.388
Monthly return	60	0.012	0.020	-0.201	0.146	0.346	0.003	0.057

7.2 Hypothesis Testing

7.2.1 Normality Testing

Table 9. Shapiro-Wilk normality test results (presentation).

Variable	W Statistic	*p*-value	Normally Distributed?
Sentiment	0.7492	0.0000	No
Communication Services	0.8324	0.0000	No
Consumer Discretionary	0.8389	0.0000	No
Consumer Staples	0.9806	0.4546	Yes
Energy	0.8070	0.0000	No
Financials	0.9452	0.0093	No
Health Care	0.9086	0.0004	No
Industrials	0.9386	0.0047	No
Information Technology	0.9365	0.0038	No
Materials	0.9413	0.0384	No
Real Estate	0.8638	0.0002	No
Utilities	0.9254	0.0102	No
Monthly return	0.9569	0.0334	No

Table 10. Shapiro-Wilk normality test results (Q&A).

Variable	W Statistic	*p*-value	Normally Distributed?
Sentiment	0.8896	0.0001	No
Communication Services	0.9635	0.1961	Yes
Consumer Discretionary	0.9372	0.0041	No
Consumer Staples	0.9722	0.1876	Yes
Energy	0.8745	0.0003	No
Financials	0.9555	0.0285	No
Health Care	0.9314	0.0028	No
Industrials	0.9086	0.0003	No
Information Technology	0.9889	0.8617	Yes
Materials	0.9483	0.0660	Yes
Real Estate	0.9494	0.0721	Yes
Utilities	0.9876	0.9274	Yes
Monthly return	0.9569	0.0334	No

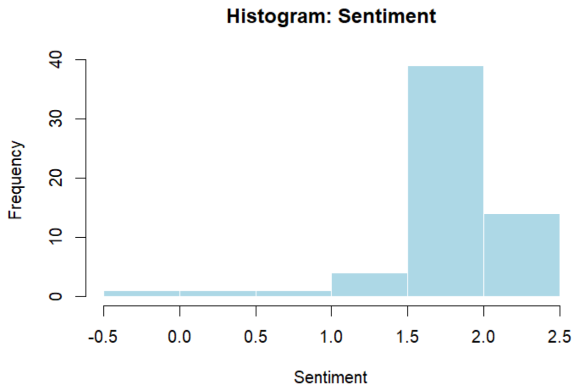

Figure 5. Histogram of 'Sentiment' variable distribution (presentation).

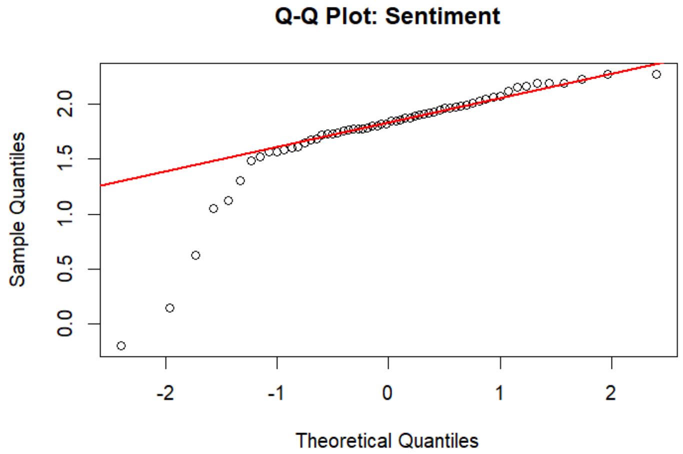

Figure 6. QQ-plot of 'Sentiment' variable distribution (presentation).

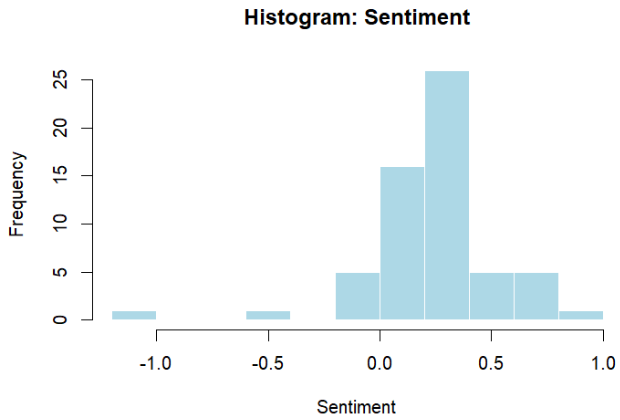

Figure 7. Histogram of 'Sentiment' variable distribution (Q&A).

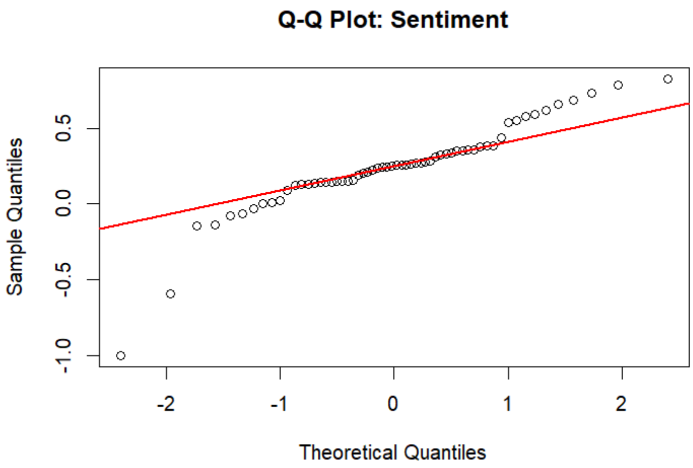

Figure 8. QQ-plot of 'Sentiment' variable distribution (Q&A).

7.2.2 Sector Analysis

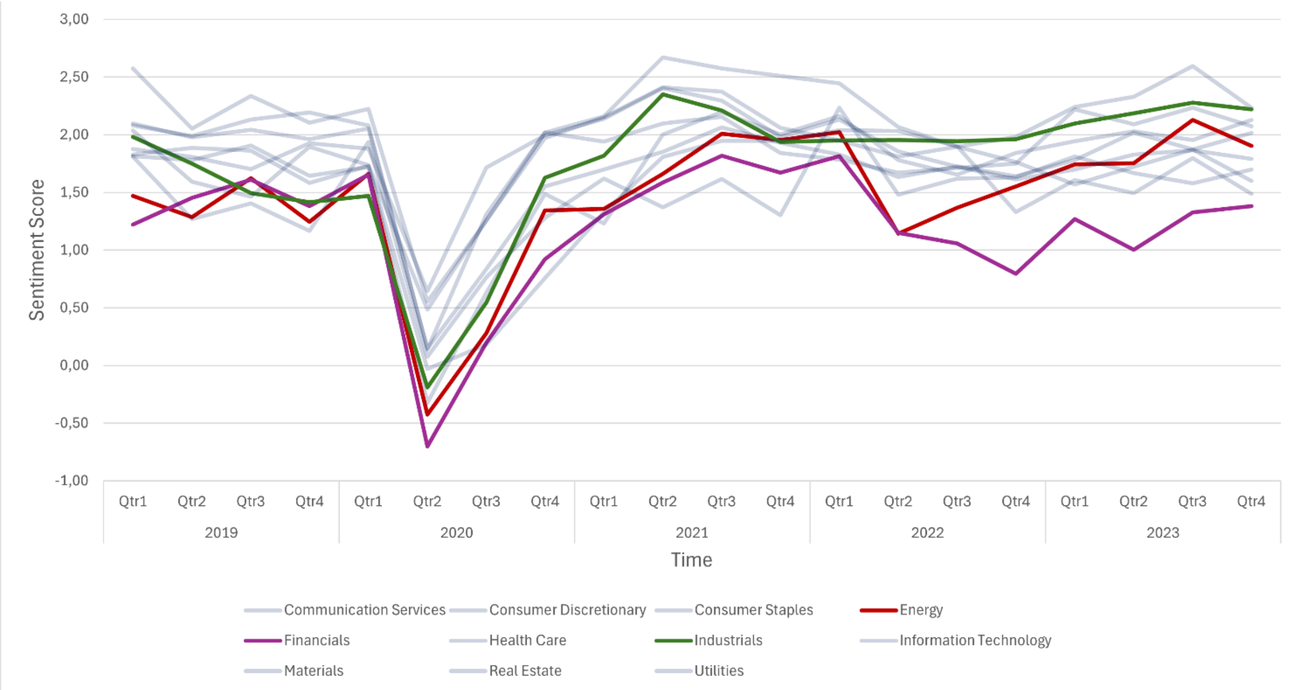

Figure 9. Hypothesized sectors in comparison to all sectors (presentation).

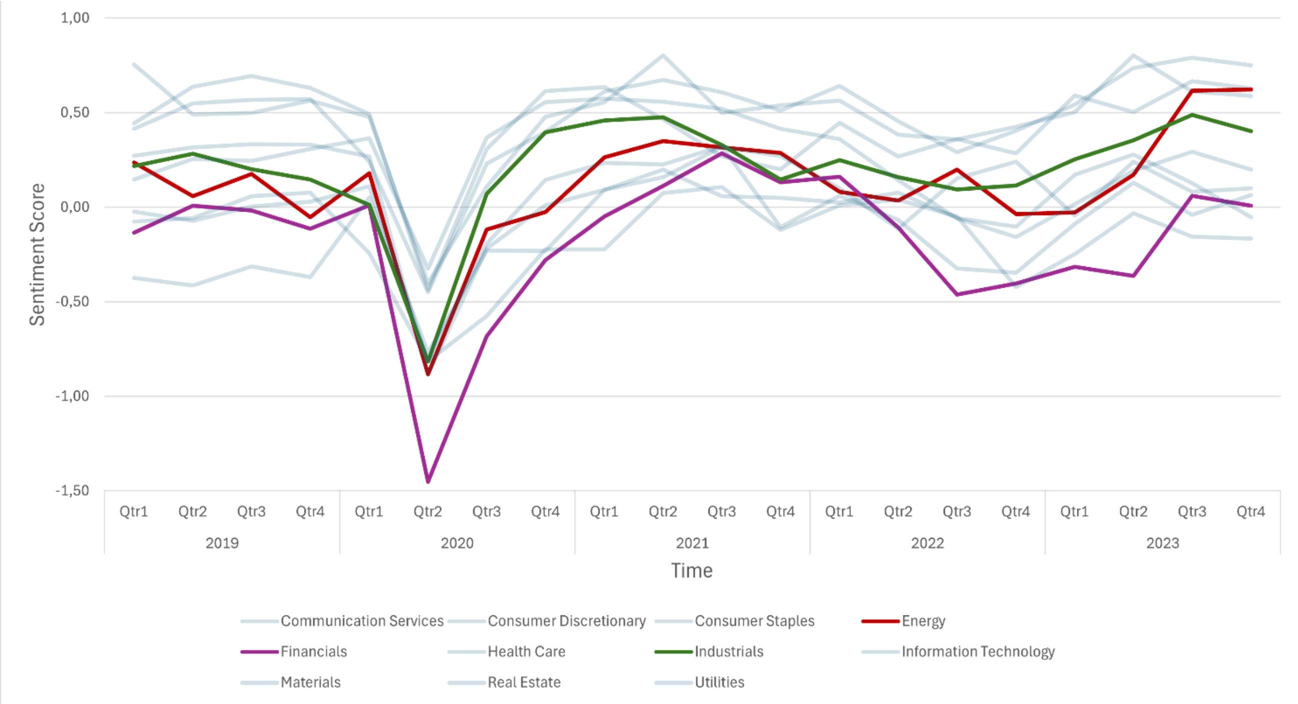

Figure 10. Hypothesized sectors in comparison to all sectors (Q&A).

7.2.3 *Time-Series Analysis*

Table 11. Pairwise Wilcoxon test results short term (Q&A).

Group 1	Group 2	Adjusted *p*-value
COVID	Pre-COVID	0.21960
Post-COVID	Pre-COVID	0.66400
COVID	COVID	
Post-COVID	COVID	0.09848

7.2.4 *Correlation Analysis*

Table 12. Robust regression results, sentiment vs next monthly return (presentation).

Term	Estimate	Std..Error	*t*.value
(Intercept)	0.0435	0.0292	1.4869
Sentiment	-0.0185	0.0166	-1.1138

Table 13. Robust regression results, sentiment vs next monthly return (Q&A).

Term	Estimate	Std..Error	*t*.value
(Intercept)	0.0170	0.0099	1.7298
Sentiment	-0.0256	0.0254	-1.0076