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Sentiment towards the COVID-19 pandemic – A valuable instrument for predicting prices in the US stock market?

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Abstract

This thesis investigates the impact of sentiment towards the COVID-19 pandemic on stock prices by incorporating sentiment into the existing Long Short-Term Memory (LSTM) model for predicting stock prices in the United States. Existing research on this field has principally been conducted before the outbreak of the pandemic, while more current studies have largely focused on overall sentiment rather than sentiment towards the pandemic. We first conduct an analysis of pandemic sentiment based on Twitter data. Sentiment scores are created from tweets following a binary approach and a categorization into eight emotions. The binary scores are then incorporated into the LSTM model to examine whether the model's accuracy in forecasting the prices of the S&P 500 index and representative stocks from each of the eleven sectors it is composed of is increased. Our analysis, conducted for the period March 1 through April 29, 2021, detects an overall positive sentiment towards the pandemic in the US, with the most prevalent emotion being trust, followed by fear. We also find that our sentiment-LSTM model outperforms the simple version of the model. Measured by MAE and RMSE, it is approximately 5% more accurate in predicting the price of the S&P 500 index, and on average approximately 20% more accurate in predicting the prices of selected stocks from the different sectors than the baseline LSTM model.

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1. Introduction

The outbreak of the COVID-19 pandemic in December of 2019 and its subsequent developments have impacted virtually any area of life all over the globe. Naturally, it has also taken a considerable toll on individuals' mental health and attitudes, which has been reflected in public sentiment toward the pandemic. Sentiment can be defined as an emotion, but also as an opinion regarding a certain issue or concept (Merriam-Webster, 2021). It can be assessed using sentiment analysis, a tool defined as "the process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer's attitude towards a particular topic, product, etc. is positive, negative, or neutral" (Lexico.com, 2021). Among other applications, sentiment analysis can be used for stock market forecasting. Existing research has already yielded interesting insights that have legitimized the overall approach of sentiment analysis and proven its relevance and usefulness for better understanding and predicting stock market reactions to public attitudes. The vast majority of such studies, however, have been performed before the outbreak of the COVID-19 pandemic. Given the considerable impact of the pandemic on public sentiment, existing analyses therefore likely have only limited applicability and relevance in this particular situation.

The pandemic has affected not only individuals' attitudes but also behaviors in a variety of areas. We believe that this also includes investment behaviors, which have likely been shaped by attitudes towards current developments of the pandemic. Existing studies have largely only investigated the value of overall sentiment for stock market prediction. On the other hand, a number of researchers have investigated sentiment during the pandemic, yet mostly without using these findings in connection with the stock market. We have, therefore, identified a need for a study that evaluates if sentiment towards the pandemic impacts stock prices, particularly also during a later stage of the pandemic. Using an approach that considers the effect of human psychology on investor behavior in an analysis of the impact of COVID-19 on the stock market seems appropriate and promising, given the strong impact that not only the pandemic itself, but also containment measures have had on mental health and opinions among the population.

We hypothesize that sentiment towards the COVID-19 pandemic influences stock prices. This hypothesis will be tested by evaluating whether a measure of such sentiment succeeds in increasing the accuracy of existing stock price prediction models. Specifically, this will be approached using a two-stage analysis, the first step of which consists of a sentiment analysis, while the second step consists of the incorporation of the obtained sentiment score into the existing Long Short-Term Memory (LSTM) model for stock price prediction. Sentiment can be retrieved from various sources, one particularly promising source being social media, specifically Twitter. Therefore, tweets will be used as the source for extracting text sentiment through the Twitter API, while stock market data will be extracted from the Yahoo Finance API. Stock market data consists of daily opening prices, daily closing prices and trading volume of the S&P 500 index as well as one stock from each of the eleven sectors the index is composed of. The analysis will focus on a period between March 1, 2021 and April 29, 2021 and will be limited to the United States.

Our analysis is an initial effort in investigating this issue and producing findings beneficial for several different parties who we consider might be interested in our research. Principally, investors as well as investment management professionals might benefit from them for the purpose of making more informed and more profitable investment decisions, while regulators might find it useful for ensuring the functioning of financial markets. Moreover, as our research aims to provide a better insight into the far-reaching effects of individual and public sentiment, both researchers and members of the society might consider our findings valuable.

This thesis will proceed as follows. Section two presents a brief review of existing literature on the topic, laying out the gap this thesis attempts to begin to fill. Section three provides an introduction into the data our analysis is based on, as well as explaining our methodology, including our choice of model and setup for the analysis. Section four presents the implementation of our analysis and our results. Section five includes a discussion and interpretation of our results, as well as an evaluation of the relevance and implications of our findings within the field. This section furthermore includes limitations of our approach and suggestions for future research. Section six will conclude.

2. Literature review

2.1 US stock market during COVID-19

In December 2019, the first case of the novel disease COVID-19 was diagnosed in Wuhan, China, marking the beginning of a global pandemic of unprecedented scale, reach and repercussions (World Health Organization, 2021b). Since its outbreak, the disease has spread across the world due to its infectious nature and human-to-human transmission. On January 30, 2020, it was acknowledged as a global public health emergency by the World Health Organization. Less than two months later, on March 11, the organization then went on to declare the outbreak a pandemic (World Health Organization, 2021b). Guidance by authorities to prevent the spread of the disease recommends social distancing, and the reduction of contact with other individuals, among other measures (Centers for Disease Control and Prevention, 2021), (World Health Organization, 2021a). This, coupled with the initially relatively unknown nature of the disease, its transmission and deadliness, lead to the imposition of lockdowns and similar measures in many countries (Financial Times, 2021).

The spread of the disease as well as the government and society's response to it have had significant psychological repercussions, which have been investigated by several researchers. In addition to the uncertainty caused by the novel nature of the disease, social behaviors such as distancing can further deteriorate individuals' mental health (Li, et al., 2020). The pandemic's impact on the world, however, goes far beyond wellbeing on an individual and collective level. As is to be expected, both the initial outbreak and major developments in the following months caused stock markets swings of almost unprecedented scale. There have been numerous studies on the effect of the pandemic on the stock market, such as Ashraf (2020), who analyzed the correlation between an increase in new case numbers and adverse stock market performance. Liu, et al. (2020) evaluated the reaction of stock markets in 77 countries to the declaration of COVID-19 as a pandemic, finding a major negative shock on the world's stock markets following the announcement. Similarly, Baker, et al. (2020) find that COVID-19 had a more significant effect on financial markets than any past pandemics with regards to US stock market volatility (Baker, et al., 2020).

Particularly the United States financial market has seen a number of remarkable developments since the outbreak of the pandemic. Coming into the year 2020, it started out with a bull market but was sent into a bear market with the global spread of COVID-19 during late February and March. It went on to rebound very quickly into a bull market, despite a recession and high unemployment in the real economy. This has been attributed to various actions by the Federal Reserve, a large-scale stimulus package and, perhaps most importantly, the fast development of a vaccine, all of which towered even over the historic 2020 presidential elections and the traditionally strong impact of major political developments on the stock market. Another interesting reason appears to be the large number of first-time individual investors, which particularly led to rising prices for tech stocks (Jackson & Curry, 2020). All of the above caused the S&P 500 index to rise 16% overall in 2020, a 60% increase from its lowest point in late March. The stock market is often considered to paint a picture of expectations for the future rather than of the present situation. This rebound is thus likely principally related to an improved outlook and overall optimism for 2021 (Udland, 2020). The overall upwards trend in the US stock market continued into the first quarter of 2021, particularly as both further stimulus packages and the headway made with the vaccine exceeded expectations. Stock market indices performed well during this period (NASDAQ, 2021). March and April 2021 saw a further return to normality in the US stock market on the back of further vaccine progress and a loosening of restrictions in the US (Silverblatt, 2021), (Rocco & Badkar, 2021).

2.2 Sentiment analysis

2.2.1 Introduction into sentiment analysis

Behavioral Economics is an area of research that incorporates perspectives from cognitive psychology in addition to conventional economic theory. Particularly, it draws on explanatory approaches from psychology to better comprehend findings from research that are not explained by traditional economic theory. As has been proven in empirical research, agents do not exhibit the rational, utility-maximizing behavior predicted by such theory. Instead, individuals appear to succumb to a number of biases and heuristics that, although psychologically necessary for decision-making under uncertainty, tend to generate irrational behavior (Tversky & Kahneman, 1974), (Rabin, 1998). A popular approach within Behavioral Economics is sentiment analysis. It builds on findings about the importance of the connection between emotions and behavior (Bollen, et al., 2011). Sentiment analysis serves to detect attitudes towards a certain topic from a written source and to quantify them into a sentiment score, which is then used to assess the impact of sentiment on behaviors (Buckman, et al., 2020). It can be conducted following either a lexical approach or machine-learning techniques. The lexical approach is based on a predefined list of words associated with an emotion, a so-called lexicon, grouped into negative, positive, and neutral categories, while machine-learning techniques aim to predict sentiment in text (Buckman, et al., 2020), (Yu, et al., 2013). There are, furthermore, two principal directions in sentiment analysis, the polarity or binary approach, and features or emotion detection. Polarity analyses categorize sentiment as negative, neutral, or positive with a score ranging from -1 to +1, while features analyses zoom in on sentiment about a specific topic in question, producing an overview that indicates the prevalence of each emotion from a predefined list according to the research focus (Yu, et al., 2013). Obtained sentiment scores can then be used in explaining a variety of phenomena by incorporating them into existing approaches in numerous fields, such as stock market forecasting.

Sentiment can be measured from different data sources, the choice of which depends on the aim of the analysis. The following overview will largely concentrate on media sources, both traditional news media and social media, as our subsequent empirical analysis is based on sentiment extracted from Twitter. The key characteristic that distinguishes social media from traditional news media is the fact that it is composed of user generated content rather than professionally published articles. In the past, conventional media as well as surveys had been a principal source for conducting sentiment analysis. However, with the rise of social media over the past years, researchers have increasingly shifted towards incorporating data from social media into their studies. Several key reasons explain this transition. Overall, the importance of other individuals' opinions as a basis for decision-making among the population has been increasing (Yu, et al., 2013). Sentiment analysis has been considered useful in displaying reviews of different businesses, products and services (Nguyen, et al., 2015). It can thus be argued that social media can be used to measure the reaction of the public, as it reflects public opinion as an aggregate of individual opinions (Yu, et al., 2013). Researchers have found that social media platforms appear to be particularly valuable for monitoring sentiment as they are real-time and contain large amounts of data, making them superior to previously common methods such as questionnaires (Li, et al., 2017). Another advantage of social media is its potentially high representativity. The fact that virtually all individuals in the world could participate can potentially lead to a significantly more diverse impression of public sentiment. Notwithstanding, naturally, not all individuals use social media. Such limitations, however, will be explored more in-depth in section 5.3. Furthermore, social media can be seen as an indirect representation of sentiment, thereby avoiding biases due to self-reporting, which can cause unnatural behavior (Bollen, et al., 2011). Data from social media thus likely reflects more natural opinions and real emotions. Nonetheless, social media sentiment should best be regarded as one factor among many for forecasting stock market developments, as will be explored in section 2.3.

2.2.2 Public sentiment during COVID-19

Over the last years, a growing number of researchers has therefore started to take advantage of the value of sentiment expressed in social media in understanding a variety of different phenomena. Given the lockdowns and social distancing measures implemented across the world, social media have arguably become more important than ever for communication amongst individuals, and hence for gaining insights into public sentiment regarding the pandemic (Xue, et al., 2020a). Due to the interconnected and globalized state of the world, the public perception of, and reaction to, the spread of the disease has generated a unique sentiment towards the pandemic. Such sentiment likely has magnified the public response and caused disproportionate shocks to virtually everything, from demand for certain consumer goods to the stock market. A number of researchers have attempted to better understand the pandemic's numerous repercussions through sentiment analysis. For this purpose, several researchers have turned to social media, especially Twitter. Twitter, a platform on which users can upload short messages on any topic, so-called tweets, which allow messages of up to 280 characters and are shared publicly, is one of the most widely used social media networks. In late 2020, Twitter had roughly 70 million monetizable daily active users based in the US (Tankovska, 2021). Twitter is the fourth most frequented website in the world and fifth most visited in the US (Similarweb, 2021). As of February 2021, 23% of the adult US population was estimated to ever use Twitter, of which 46% use it daily (Pew Research Center, 2021). In addition to its valuable insights into trending issues and opinions, Twitter is popular among researchers as it contains an application programming interface (API), which provides researchers access to considerable data on published tweets (Nisar & Yeung, 2018).

To a certain extent, Twitter sentiment analysis has been able to capture the considerable impact of the pandemic on public sentiment. Xue, et al. (2020a) set out to understand psychological reactions of English-language Twitter users to the pandemic between late January and early March 2020. Their research shows that there was a prevalence of COVID-related fear and a minor increase in the prevalence of trust over time, while an increased number of COVID-related tweets appeared to coincide with major pandemic developments (Xue, et al., 2020a). Similarly, Samuel, et al. (2020) analyzed Twitter sentiment in the US during February and March of 2020. The study found mixed sentiment in the early weeks, while fear and generally negative sentiment began increasing towards the end of March (Samuel, et al., 2020). Xue, et al. (2020b) evaluated opinions about the pandemic published on Twitter between March and April 2020. Key sentiments identified in this study included anticipation for improvement through government and healthcare industry response as well as overall fear (Xue, et al., 2020b). As demonstrated by such studies, sentiment analysis appears to be a valuable instrument for gaining insights into the effect the COVID-19 pandemic has had on public opinion and emotions. Particularly fear appeared to be a dominant emotion during the early months of the pandemic.

2.3 Sentiment analysis for stock market forecasting

2.3.1 Sentiment before COVID-19

A principal area of interest in the application of sentiment analysis is the stock market. Researchers' interest in this application of sentiment analysis can largely be attributed to a key puzzle in financial theory, namely asset pricing. A key concept within this field is the Efficient Markets Hypothesis (EMH), which holds that in an efficient market, prices of securities always include available information (Fama, 1970). Conventional theory thus assumes that enterprises are priced solely according to the discounted value of expected future cash flows, thereby assuming rationality of investors (Baker & Wurgler, 2006). However, numerous studies on the topic have shown that this hypothesis is not confirmed empirically, as prices deviate from those predicted by the traditional theory (Ritter, 2003). The field of Behavioral Finance consists of approaches for explaining irrational behaviors in financial markets using notions from psychology. A key notion within this area is investor sentiment, which can be defined as "a belief about future cash flows that is not justified by facts at hand" (Baker & Wurgler, 2007, p. 129). One could argue that the term was established by De Long, et al. (1990), who initially introduced it through the concept of so-called noise traders, as opposed to sophisticated investors, whose irrational behavior due to optimism or pessimism generates risk that causes prices to deviate from their fundamental, i.e., rational, values. This change was found to be unpredictable and therefore generally not arbitraged away. Such an approach helps in explaining a variety of empirical findings that are not consistent with traditional asset pricing approaches (De Long, et al., 1990). Research on the topic of investor sentiment has been conducted using various different sentiment indicators, all of which have certain advantages and disadvantages. Such measures include surveys, mood proxies, and a variety of financial measures such as trading volume, option-implied volatility or returns on the day of an IPO (Baker & Wurgler, 2007).

During the last years, extensive research into investor sentiment and its usefulness in better understanding and predicting the stock market has emerged. As stock prices often do not only reflect a company's fundamental value and, furthermore, tend to fluctuate significantly, they are difficult to forecast. Such volatility often stems from a number of sources external to the company itself, which impact prices. These include the state of the economy, political developments and other aspects such as financial market trends (Mohan et al., 2019). Stock forecasting is particularly popular among investors, as accurate predictions allow for more profitable and sustainable trading behaviors, given the overall rather unpredictable nature of prices (Chou et al., 2021).

Baker & Wurgler (2006 and 2007) made important contributions to the field of investor sentiment, as their 2006 study offered proof of the fact that sentiment appeared to, in fact, influence the stock market, and therefore of the value of sentiment analysis within finance (Baker & Wurgler, 2006). Their 2007 research presented several interpretations and implications of investor sentiment. The authors show that sentiment seems to affect both single companies' stocks and the market as a whole. On the firm level, Baker & Wurgler found that sentiment appears to affect certain types of companies more than others, particularly those that are harder to value due to higher uncertainty, giving more room for interpretation according to sentiment (Baker & Wurgler, 2007). On the market level, the authors suggest that one can argue that sentiment might have been what created bubbles in the past, as bubbles generally coincided with peaks in the sentiment index developed in Baker & Wurgler (2006). In their research, the authors measure sentiment with an index reflecting different financial measures, such as share turnover (Baker & Wurgler, 2006).

Within media sentiment, on the other hand, one important area of research is dedicated to assessing the relationship between conventional news media and the stock market. Following this approach, Tetlock (2007) finds that news is useful for predicting stock market movements and that increased pessimism in the media impacts trading in the US stock market, both with regards to prices and trading volume. According to the study, negative sentiment appears to be a valuable tool for predicting downturns in stock markets, particularly for small stocks. In line with this, only little evidence was found for the assumption that negative sentiment contains new information important for the fundamental value of a stock that has not yet been reflected in its price (Tetlock, 2007). Despite its significance for the field of Behavioral Finance, such research does not consider relevant timely data such as those available from social media (Li, et al., 2019). Studies including data from both traditional news media and social media generally find that sentiment found in social media appears to have a more significant effect on stock prices than that found in traditional media, see, for instance, Yu, et al. (2013) or Gan, et al. (2019). Thus, increasingly, researchers have also begun to utilize social media data as the sole basis for sentiment analysis. Several different social media sources have been used in existing research.

Karabulut (2013) evaluates the usefulness of Facebook's Gross National Happiness index, which is based on sentiment extracted from user status posts, for forecasting US financial market developments. The study shows that the index is useful for forecasting trading volume as well as movements in returns. Changes in returns appeared to be temporary and reversed entirely in the two subsequent weeks after the change occurred. Stock market changes that coincided with changes in sentiment were found to reverse over the long run, implying that the market was reacting to sentiment rather than incorporating new fundamental information, which would cause a persisting change. These results were also confirmed in both the UK and Germany (Karabulut, 2013).

As one of the most frequented social media sites, several researchers have also turned to Twitter to extract sentiment used for understanding and forecasting stock market developments. The importance of Twitter for official communication by companies as well as for the publication of investor opinions on financial developments has become undisputed in recent years, legitimizing the platform's role within the financial world (Broadstock & Zhang, 2019). Bollen, et al. (2011) investigate the relationship of Twitter sentiment to the Dow Jones Industrial Average (DJIA), using both a polarity approach as well as measuring specific emotions. The study shows no predictive quality of the binary sentiment classification. However, a calm sentiment appeared to forecast the DJIA with the change presenting itself three to four days later (Bollen, et al., 2011). Similarly, Ranco, et al. (2015) studied the impact of binary Twitter sentiment, showing a dependence between social media sentiment towards a company and its share price. This study furthermore found that aggregate public sentiment seemed to indicate whether the DJIA subsequently moved up or down (Ranco, et al., 2015). Zhang, et al. (2011) set out to assess whether the performance of market indices could be forecasted using Twitter sentiment. The researchers found that words referring to an emotion appeared to increase during uncertain economic situations and that generally, more emotional tweets, containing hope, fear, and worry, on one day seemed to coincide with the Dow Jones going down the following day. When tweets did not refer to these emotions, the Dow Jones appeared to go up the next day (Zhang, et al., 2011).

In addition to stock market indices, some researchers have directed their efforts at sentiment analysis for forecasting prices of individual stocks. Checkley, et al. (2017) focus on evaluating the value of Twitter sentiment for predicting stock price developments of five US companies. The study shows that sentiment appeared to be useful for forecasting the direction of the share price movements and, even more so, for volatility and trading volume (Checkley, et al., 2017). Broadstock & Zhang (2019) explore the impact of Twitter sentiment on equity prices for six companies in the US, detecting a significant impact of sentiment on the companies' stock prices, which appeared to occur with a lag (Broadstock & Zhang, 2019). Yuke, et al. (2017) took the approach of using media sentiment one step further and attempted to improve a momentum strategy by including sentiment from news and social media. The study's results show that incorporating sentiment improved the momentum strategy's profitability (Yuke, et al., 2017).

Only a few studies have investigated public sentiment regarding a specific event. An example of this is Nisar & Yeung's 2018 research, conducted with a data sample, which looked at Twitter sentiment regarding political developments and its link to the movements of a stock market index during a six-day period centered around the UK 2016 elections. The study detected that increased discussion about political topics appeared to cause a decreased closing price, which the authors hypothesize could potentially be attributed to increased uncertainty and decreased trust. The study, furthermore, found a correlation between sentiment about the election and stock prices as well as proof of causation in this relationship (Nisar & Yeung, 2018).

The abovementioned examples of research are based on different approaches for evaluating the role of sentiment for stock market prediction. However, over the last years, particularly machine-learning approaches for stock market forecasting have grown in popularity. One such approach is the Long Short-Term Memory (LSTM) model. It essentially consists of a deep-learning approach which uses historical prices, the training data, for stock price prediction in the testing data (Hochreiter & Schmidhuber, 1997). The model and the way it functions will be explained more in-depth in section 3. Several researchers have made efforts to refine the base model by including a sentiment variable, retrieved from different sources, to increase its forecasting precision. Mohan, et al. (2019) evaluated the performance of several existing forecasting approaches, including the ARIMA, also explained more closely in section 3, and the LSTM model, by adding a financial news sentiment variable. The authors analyzed a five-year period of the daily prices of all S&P 500 companies' stocks, finding that the LSTM model with the addition of a binary sentiment score returned the most accurate prediction overall, although it was less precise for highly volatile and low-prices stocks (Mohan, et al., 2019). Hiew, et al. (2019) investigate, among other things, the value of including a binary textual sentiment index based on Weibo, the Chinese equivalent of Twitter, into the LSTM model for predicting the prices of three stocks traded on the Hong Kong Stock Exchange over three years. Their study shows that the model's forecasting ability is improved by their sentiment index on a yearly basis, while being less accurate over the whole three-year period (Hiew, et al., 2019). Similar approaches are followed also for forecasting volatility, see, for instance, Liu, et al., (2017) or Xing, et al. (2019) as well as for predicting the prices of cryptocurrencies, as, for example, Huang, et al. (2021) and Pant, et al. (2020). Overall, the research discussed above clearly signals the value of sentiment analysis for increasing the precision of existing approaches to stock market forecasting.

2.3.2 Sentiment during COVID-19

As has become clear, quite an extensive body of research has been dedicated to utilizing sentiment analysis in connection to different stock markets. The vast majority of this research has been conducted before the COVID-19 pandemic. However, we suspect that there is a stronger impact of sentiment on investment decisions during such an unusual time. A growing number of researchers have taken to social media to conduct a sentiment analysis for predicting stock prices during COVID-19. For instance, Xia & Chen (2021) look at emotions extracted from Twitter to refine an existing prediction model, finding that such sentiment does increase the accuracy of prediction. Chou et al. (2021) incorporate sentiment scores from Twitter, among other sources, as well as a measure of attention into the LSTM model for predicting the price of one stock during the entire year of 2020. Their study moves away from binary sentiment scores by creating a mechanism of classification of tweets as either bullish or bearish using LSTM. The authors find that especially the model including both sentiment and attention achieves a higher prediction precision than the traditional approach (Chou et al., 2021).

Research in this field has to date largely only analyzed how useful overall sentiment is for forecasting stock prices. However, we believe that particularly sentiment towards the pandemic itself is a valuable tool for predicting stock market developments. The COVID-19 pandemic has shaped individuals' attitudes, and likely their decisions and actions. We suspect that this also holds true for investment behaviors, which we assume have been impacted by individuals' opinions and feelings towards the pandemic. Only a few studies have investigated this topic. For instance, Baker et al. (2020) find that both positive and negative COVID-related news from traditional newspapers appeared to be an impactful force on the US stock market between February and April 2020, both with regards to volatility and large moves in the market. The authors detected not only strong but also very frequent jumps between late February and March 2020, the majority of which appeared to be linked to news about the pandemic. Additionally, COVID-19 news sentiment appeared to cause one of the strongest spikes in volatility since 1900, which persisted from January onwards, without having returned to pre-pandemic values even in late April 2020 (Baker, et al., 2020). Similarly, Costola, et al. (2020) evaluate the impact of COVID-19 news sentiment on stock market returns, finding a positive correlation between binary sentiment scores and S&P 500 returns. (Costola, et al., 2020). Lee (2020) investigates news and Google sentiment towards COVID-19 between January and May 2020, finding a correlation of such a sentiment measure with sector indices in the US to a varying degree, depending on the industry. Goel, et al. (2021) analyzed whether COVID-19-related tweets referring to the word "stock" between February and May 2020 appeared to coincide with changes in the log returns of US stock market indices. Their study showed that returns appeared to decrease at the same time as the relative number of pandemic-related tweets referring to stocks increased (Goel, et al., 2021). Zammarchi, et al. (2021) found that Twitter sentiment towards Italy during the early months of the pandemic was valuable for forecasting movements of the Italian Stock Exchange's principal index. Jabeen, et al. (2021) create a binary score of Twitter sentiment towards COVID-19, which is added into the LSTM model, finding an increase in accuracy. However, their analysis only considers five US American stocks within each of the five industries that are believed to be most impacted by the pandemic, such as airline and pharmaceutical companies and was conducted on data ending in April 2020, shortly after the outbreak of the pandemic.

2.4 Gap in the literature

Given the existing literature laid out in the abovementioned, we have identified a gap in the research on this topic. To the best of our knowledge, there does not appear to be any research utilizing Twitter sentiment towards the COVID-19 pandemic for forecasting stock prices during a later phase of the pandemic, particularly taking a market-level approach. Most research on using sentiment analysis for forecasting stock market movements has been created before the outbreak of the pandemic, thereby limiting its applicability and relevance to the current situation. Several key characteristics distinguish the current situation from pre-pandemic times. Principally, we suspect that the exact sentiment prevalent during the pandemic is different from sentiment in non-crisis times. Similarly, we believe sentiment during the early months of the pandemic differs from sentiment during its second year, thus also potentially changing its impact on stock prices. Moreover, although certain studies have analyzed sentiment towards a particular event, such as the COVID-19 pandemic, these findings have generally not been utilized for forecasting stock market developments. The body of research that considers sentiment as an additional variable to be incorporated into existing stock price prediction models has, to date, largely utilized overall sentiment rather than sentiment towards a certain event. Also, those analyses conducted after the outbreak of the pandemic to forecast stock market movements have focused on sentiment during the pandemic rather than towards it. However, given that there have been other important developments in the world and in the United States, such as the 2020 presidential elections, we believe that overall sentiment does not coincide exactly with sentiment towards COVID-19. Thus, we expect to gain additional insights from our approach to investigating the relationship of COVID-19 sentiment and stock prices. A particularly promising source of sentiment data appears to be social media, and specifically Twitter. Therefore, in the following, we are going to evaluate whether public sentiment towards the pandemic, as reflected on Twitter, increases the accuracy of stock price prediction using the LSTM model in the US during a more advanced stage of the pandemic.

3. Data and methodology

We hypothesize that sentiment towards the COVID-19 pandemic impacts stock prices, also during a more advanced stage of the pandemic. We will test this by including a binary sentiment score into the existing long short-term memory (LSTM) model for predicting the prices in the US stock market, which will be assessed using the S&P 500 index and the stock with the highest market capitalization within each of the eleven sectors the index is composed of, in March and April of 2021. In order to do so, we will proceed with a two-step analysis. The first step involves the sentiment analysis, which will both give a binary assessment, determining whether overall sentiment towards the pandemic is positive or negative, and investigate which emotions are most prevalent in public sentiment. In the second step, the obtained sentiment score will then be included into the LSTM model. The refined model is trained with data from March 1 through April 9, 2021 and then tested against both the standard LSTM model and another alternative approach, the ARIMA model with data from April 12 through 29, 2021. Before presenting our analysis, we will firstly explain more closely how we obtained the data for our research. Tweets are the major input for the analysis of sentiment towards COVID-19 pandemic. Twitter data is generated through Twitter's application programming interface (API) using the programming software R. Stock market data, on the other hand, is generated through Yahoo Finance's API, again utilizing R. In the following, we will explain the models used for the analysis and the methods used to apply the prepared data into the models.

3.1 Data collection and processing

According to our two-step approach, the data collection section also has two broad parts. The first part explains the extraction and processing of Twitter data for sentiment analysis. In addition to this, it also presents a brief insight into how we ensured to measure only sentiment towards the COVID-19 pandemic rather than overall public sentiment. For this purpose, we have used a number of keywords related to the pandemic, which will be presented here as well. We then record the sentiment score, which is subsequently normalized for comparison with the market index performance. The second part looks at the stock market data, the S&P 500 index and one stock from each of its sectors, which includes the collection and processing techniques to make them suitable for the financial time series analysis.

3.1.1 Twitter data collection

In the first step, we registered for a developer account offered by the Twitter API, through which we can connect the R console to Twitter, and then gathered tweets from Twitter's API for every day during the period March 1, 2021 to April 29, 2021. The data extraction is limited in two ways to ensure that only those tweets published in the US and containing statements of sentiment towards the pandemic are retrieved. Since in this thesis, we perform sentiment analysis to understand how the tweets in the US regarding the pandemic impact the dominant stock market, we integrate text mining of the data on a country level. Although the worldwide pandemic has become more complex during April, especially in the Asian area, we only consider the situation within the US. In addition, only a small portion of the tweets concerning the foreign pandemic situations are written in English, which means that it likely would not make a significant difference if more foreign-event hashtags were included. Hence, we will limit our analysis to the most representative and often-quoted hashtags.

Most pandemic-related tweets feature the hashtag "covid-19" (Samuel, et al. 2020). However, to achieve a more comprehensive collection of tweets containing information about sentiment towards the COVID-19 pandemic in addition to those including the COVID-19 hashtag, we integrated a list of representative keywords for the extraction of tweets, based on the most updated studies of COVID-19 tweet data and on other similar articles analyzing pandemic sentiment (Xia & Chen, 2021; Ko & Chang, 2021). These words appear in the text of tweets with the highest frequencies and hence could guarantee that the tweets used in our analysis all referred to COVID-19 and closely related events. An overview of the keywords can be found in Table 1. The "rtweet" package in R allows us to filter the tweets accordingly. The "search_tweets" function in the package can filter and select tweets containing at least one of the keywords or phrases from the Twitter API. We input the keywords as the query (q) in the function. In order to make sure all the available tweets are selected, we specify the integer (n) to a large number and set the "retryonratelimit" argument in the function to “TRUE” to automate the process of conducting big searches. In this way, the progress waits and retries every 15 minutes when a rate limit of 18,000 tweets is reached. Typically, for many search queries, there will not be more than 18,000 tweets to return.

Pandemic / Daily-Life-related Words (case ignored)			
covid-19	covid	coronavirus	sars-cov
stay home	work from home	testing site	quarantine
mask	pandemic	lock down	Wuhan
toilet paper	social distancing	vaccine	community spread
N95	KN95	transmission	

Table 1: Keywords used to retrieve tweets containing sentiment towards the COVID-19 pandemic

Table 1 shows a list of keywords or phrases that must appear at least once in a tweet for it to be selected as a COVID-19 tweet for sentiment analysis. The list is based on similar sentiment studies and consists of those words that are assumed to be highly relevant to the COVID-19 pandemic. *Source: Own elaboration.*

3.1.2 Twitter data processing

After collecting the tweets, the raw data is processed and prepared for analysis. The cleaning step of the Twitter data is based on the sentiment analysis studies conducted by Samuel, et al. (2020) and Xia & Chen (2021). The raw data is filtered to subsets focusing on tweets tagged with the US as a country through the use of geocode to indicate the parameters of latitude, longitude and a radius, based on Dewald (2015). Then, we further clean the data for the analysis, which includes deleting null, meaningless values, and strange characters. We also delete both replies and retweets since we aim to focus only on original tweets. The data of time of the tweets under the “created_at” volume is arranged into a standard form. After the initial cleaning of the data, we obtain a data frame with 50 columns including, among other data, user ID, creation time, source device and text. An illustration of the table with the first six variables can be seen in Figure 1.

	user_id	status_id	created_at	screen_name	text	source
1	239857777	1384894535315169282	2021-04-21 15:39:21	Indira_L	Yes, #vaccines block most transmission of #COVID19 ...	Twitter Web App
2	473065788	1384894496924741633	2021-04-21 15:39:12	fable_e_greene	@DisneyDan my high school production in 2012 is by...	Twitter for Android
3	1347974279686713344	1384894445460594689	2021-04-21 15:39:00	tudhunc	@xfriendlyghost @hummdog94 @thehill There is evid...	Twitter for iPhone
4	1347974279686713344	1384256166960656386	2021-04-19 21:22:43	tudhunc	@xfriendlyghost @hummdog94 @thehill Long-term e...	Twitter for iPhone
5	104376010	1384894393052762114	2021-04-21 15:38:48	Cabooster	The other day they burnt the crawfish and caused a ki...	Twitter Web App
6	1037415051546771458	1384894212454371329	2021-04-21 15:38:04	EdBayne1	@Jessicam6946 @Patrici79474255 I'm so sorry, Jess. ...	Twitter Web App
7	264354845	1384894018199379971	2021-04-21 15:37:18	the_GNCC	Join us April 22nd for news on COVID-19, vaccination...	Sprout Social
8	930825032808398848	1384893962574602242	2021-04-21 15:37:05	ReadEarlyDaily	Look what one customer wrote about us: I am extre...	Twitter Web App

Figure 1: An illustration of the Twitter data collected from the Twitter API

Figure 1 shows part of the tweets' information collected from the Twitter API, which includes the first 6 variables: user ID, status ID, creation time, screen name, text, and source of device. There are 50 variables in the table in total. The text column and the time column are of the most importance, as they constitute the basis for our sentiment analysis. *Source: Twitter data.*

The columns containing text and creation times are most essential to our analysis. Based on this data, we then proceed with performing the sentiment analysis to generate sentiment scores. The "ts_plot" function in the "rtweet" package can plot a line chart of tweets by volume over time. We called the argument "by" to differ the columns of tweets by day. Based on the chart, we can show the daily frequency of tweets which can give us an overall understanding of the activity of the Twitter accounts. We detected that the distribution of COVID-related tweets is moving within a certain range without abrupt extreme changes in occurrence numbers, which may indicate that during this period, the COVID-19 sentiment on Twitter and the pandemic event in real life were both relatively stable. The plot of tweets by volume is shown in Figure 2. The volume of tweets would not affect the sentiment score because the daily COVID-19 related tweets are then aggregated and assigned an average sentiment score. Hence, plotting the tweets by volume allows us to have an overview of the Twitter reactions during the research period which could not be reflected by the sentiment scores. In addition, in a situation where the tweet volume fluctuates significantly, which is not the case for our research, it would be important to normalize the sentiment scores for volume or even consider the tweet volume as a variable for the stock prediction models.

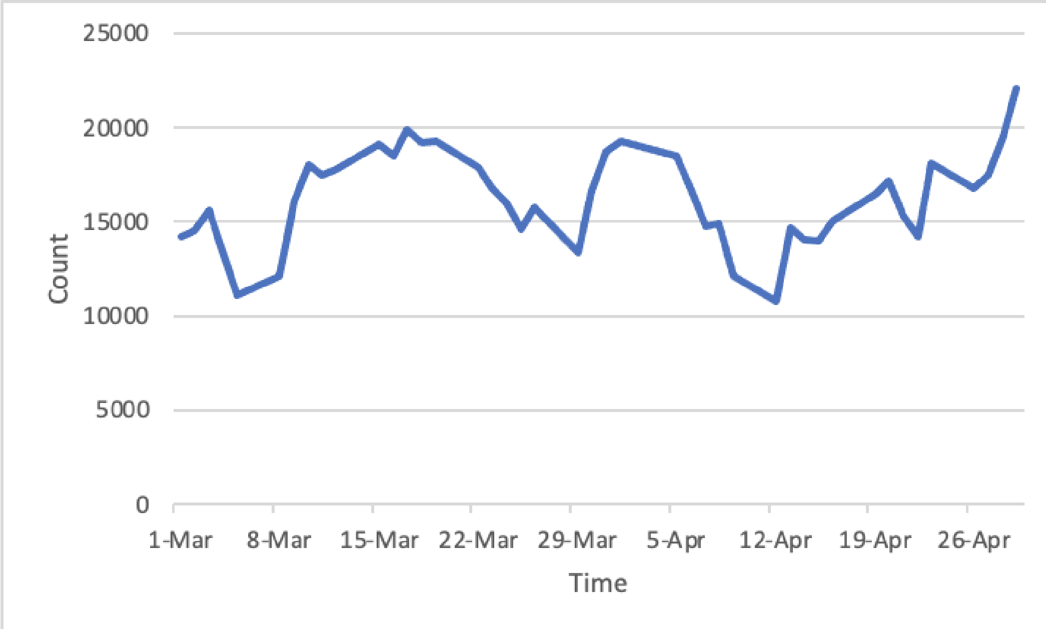

Figure 2: Daily frequency of COVID-related tweets

Figure 2 depicts that the number of tweets related to the pandemic in the US between March 1 and April 29, 2021 was relatively stable with a frequency ranging from 11,000-20,000 tweets per day. *Source: Twitter data processed in R.*

3.1.3 Stock price data collection

We use the Yahoo Finance API to obtain the past stock data, specifically daily opening prices, daily closing prices and trading volume of the S&P 500 index and the selected companies from the eleven sectors. The market index used in this research is the S&P 500 index, which is considered a major index for the US financial market. Standard & Poor's (S&P) sort firms into eleven different sectors according to their primary business activities. This categorization is known as the "Global Industry Classification Standard" (S&P Dow Jones Indices, 2021a). For each sector, we also selected the company with the highest market capitalization for our analysis, as there is generally more available information and discussion around those companies. The sectors, company names and their ticker symbols can be seen in the tables in the appendix. We chose to include this additional data in order to study whether sentiment analysis can help to improve the forecasting for individual stocks and how companies in different industries are influenced by COVID-19 sentiment on Twitter. The S&P 500 index constitutes the top 500 listed US companies, according to the rank of market capitalization and liquidity across all industries. Hence, it is relatively representative for the overall stock market prices as well as relatively risk diversified. The S&P 500 index also has the advantage of reflecting the actual value of company stocks and the fluctuation of the whole financial market as it is weighted by market capitalization (S&P Dow Jones Indices, 2021b).

The stock market data includes void value on days where the stock market is not open but still has trading activities occurring, such as on weekends and holidays. Xia & Chen (2021) used Lagrangian interpolation to substitute the missing data. However, in our research, we will not fill in this data because investors cannot trade on holidays or weekends at an interpolated price and most of the clean datasets would have no data on those days. Investors trading on days for which the trading prices are assumed is only an imaginary event. In addition, the assumptions on missing days would be inaccurate especially for high volatility stock data. Hence, we will exclude those data in our analysis.

3.1.4 Stock price data processing

Then, we further clean the stock price data for the research. Since financial time series data of daily stock prices has constant and relatively random fluctuations due to noise, autocorrelation, and seasonality (Jiang, et al. 2020), we must denoise the data for the later forecasting part. In the conventional approaches for predictions, the moving averages and differencing are used to decrease the noise in the stock price data and increase the accuracy of the prediction. Hence, we prepare our stock data through the differential method which consists of obtaining the difference between two consecutive data values in the time series. It removes components in the data that are time dependent. Modeling using the difference, rather than the raw values, aims to increase the model's predictive power (Wanjohi, 2018). In our research, we will compare the performance of our refined LSTM model to the traditional LSTM and the ARIMA model. In the LSTM model as well as our adjusted LSTM model, we used the differencing method (the "diff ()" function in R) to prepare the time series of closing prices. In the ARIMA model, the "I" (integrated) represents the degree of differencing that makes the time series data stationary which will be decided by the "auto.arima" function according to the AIC and BIC value. We use the Ith time differencing to prepare the raw data. An explanation of the models will be shown in section 3.3.

3.2 Stock prediction methods

The obtained and cleaned data is then used to assess if the COVID-19 sentiment scores from Twitter can be used to predict the stock prices. In this section, we will explain both the models utilized in our analysis and related methods of stock price prediction.

As discussed in the literature review, the well-known Efficient Market Hypothesis assumes that prices are unpredictable in an efficient market. In a nutshell, the EMH holds that all available information today is already reflected by market prices and that therefore, one cannot beat the market. However, many studies have shown that there are contrasts to the classic financial market data properties, such as the properties of stationarity, linearity, and independence. The financial data follows fractal patterns and trends as well as displaying momentum effects. This, therefore, implies that markets are not efficient after all. Therefore, there are many advanced methods in both Finance and Economics to forecast stock prices, with the Financial Time Series (FTS) being the most prominent one (Tsay, 2005). Among the various financial forecasting methods, the financial time series and projection is the driving force behind the traditional forecast methods (Tan, 2020). It includes studying historical data and detecting patterns and structures through the dynamics of the data. It furthermore involves the use of models of linear, nonlinear, and machine learning-based nature to study and predict the non-stationary, non-linear, and noisy financial time series. One shortcoming of FTS worth mentioning here is that some academic publications of FTS forecasting can be misleading and inaccurate, as often, such studies expand their model for recognition, but only wind up overfitting their approaches with excessive usage of simulators (Tan, 2020). Another factor to take into consideration is that many of the performances claimed in these papers are difficult to replicate as they fail to generalize for future changes in the special FTS being forecast. In the recent investigation of the time series of data in the financial markets, deep learning models are introduced for stock price forecasting (Tan, 2020; Jiang et al. 2018). Such models consist of a class of machine learning algorithms with an addition of multiple layers and can gradually obtain higher-level elements from raw data.

One of such models, the LSTM network, was proposed in 1997 by Hochreiter & Schmidhuber. Compared with regression predictive modeling, the LSTM time series approach addresses the complexity of sequence dependence among the variables of inputs. The recurrent neural network

(RNN) is designed to solve the problem of sequence dependence. The LSTM network is a kind of RNN in deep learning which can train large architectures and process the time series data through proliferation research. Since the LSTM model can store information for a relatively long time, it is effective when dealing with time series data with sequential dependence. When applying the LSTM model, one has the flexibility to decide which information is to be stored or discarded. Due to those characteristics, the LSTM model is often used to solve common issues with stock price forecasting (Hochreiter & Schmidhuber, 1997).

However, the prediction power of deep learning in FTS is still far from enough (Xia & Chen, 2021). The algorithm of LSTM has been shown in many papers to be sufficiently strong in dealing with serial financial data (see, for instance, Gao, et al., 2017 and Liang, et al., 2019) but the predicting power of LSTM for stock analysis could still be improved (Liang, et al. 2019). Since deep learning functions on the basis of past data, it does not perform well in predicting stock prices in a changing market, where it may produce negative long-term returns in practice. This, therefore, calls for a better method to introduce existing analytic algorithms to the financial time series analysis. Haroon & Rizvi (2020) state that sentiment analysis might be a good means of access for applying analytic algorithms from other fields to the financial market as the mathematical mechanism of stock prices can be highly complex due to a large variety of stimulations. To better detect the patterns of stock market data, Schumaker & Chen (2009) investigated how changes in stock prices were connected to changes in the emotions of investors. Following this approach and using sentiment analysis as a way of adding algorithms into the analysis of financial markets, it is then crucial to select the most suitable model to integrate the sentiment component into. The LSTM model appears to be a suitable choice, as has been proven by several researchers, also presented in the literature review, who explored the accuracy and adaptability of this model in more detail as well as further developing the model itself. Importantly, in 2017, the LSTM was refined by Graves, et al. with the addition of a time-weighted function. Qiu et al. (2020) proposed an LSTM based on attention in their research, which combines the traditional approach with an attention mechanism. The authors showed that there was a significant advantage of such an incorporation when compared both with the traditional LSTM model and with variations of it, such as the LSTM model with wavelet denoising, as well as with other related models, such as the gated recurrent unit (GRU) neural network model. Jiang et al (2018) compared the LSTM approach with the RNN and detected that the LSTM model achieved superior results in stock forecasting. The authors proposed a series of hybrid networks to predict the stock price trends formed on the sequence of current news, showing that their experimental models significantly outperformed a series of multi-task models and achieved the best result. Overall, it thus seems that the LSTM combined with attention measures is more accurate than the traditional LSTM as its distinctive structure impedes lasting dependencies.

3.3 Functioning of prediction models

In this thesis, we propose a refined version of the LSTM model which incorporates sentiment scores in addition to the historical stock prices. In the following, our adapted model will be referred to as Sentiment(S)-LSTM. We will use the S-LSTM to test the hypothesis that we made about the connection between sentiment and stock prices under the COVID-19 pandemic. In addition to the S-LSTM approach, we will also include two additional, similar models to compare the accuracy of our approach to, and thus to better interpret our findings. Therefore, in our analysis, we will utilize the following three stock market forecasting models, the ARIMA model, the conventional LSTM model, and our refined S-LSTM model. These models use the same data sets both for training and testing the data under the same operating circumstances with different extent of data processing due to the models' structures. The way these models function will be presented briefly in the following.

ARIMA (AutoRegressive Integrated Moving Average), defined by Box, et al. (1970), is a common statistical model used to analyze as well as predict time sequence data. The ARIMA (p, d, q) method consists of three parts: 1) the autoregression (AR), which captures a time dependence between an observation and that observation's certain p-lagged values; 2) the integrated (I), which is the extent of differencing (d) aimed at making the data stationary; 3) the moving average (MA), which creates a relationship between an observed value and a residual error resulting from a moving average approach employed for the q-lagged observations (Box, et al., 1970). We utilize "auto.arima" in the R forecast package to automatically form the suitable ARIMA (p, d, q) model for the time series of each stock price according to the AIC and BIC values. The information criteria of AIC and BIC are included in the "auto.arima" function. Then we use the "forecast" function for making predictions. The Akaike Information Criterion (AIC) and Schwarz-Bayesian

Information Criterion (BIC) are the criteria which are used to determine the order of an ARIMA model (Box, et al., 1970). Typically, for some predefined P and Q (we set P=10 and Q=10 in our research), we compute AIC and BIC for the ARIMA(p,q) models, with $0 \leq p \leq P$ and $0 \leq q \leq Q$, and select the one that returns the lowest value of AIC and BIC. There is no evidence suggesting one criterion outperforms the other. Hence, by indicating the information criteria in the "auto.arima" function, we select the ARIMA model which gives the relatively smallest information criterion.

As introduced above, the LSTM model is a type of RNN that applies deep learning, utilizing the output of a state as input to retain it from one iteration to the next. In our research, we use traditional LSTM neural networks based on studies by Chen, et al. (2016) and Gao, et al (2017), from which we have taken the below-mentioned steps. The programming of this model is essentially based on certain inputs along with internal variables. The LSTM excels in assessing relationships between time-series data via its memory function due to its strong memory storage capacity. The memory block of LSTM is known as cells where the information is contained in the cell state C_t and the hidden state h_t and is regulated by gate mechanisms through sigmoid and tanh activation functions. The sigmoid function controls the information adding and deleting through output numbers within the range of [0, 1], where 0 means that nothing goes through and 1 means that everything goes through. In a nutshell, the gates take the current input x_t and the hidden states from the previous step h_{t-1}, then multiplies them pointwise by weight matrices W and adds a bias b to the product. The formula for each gate, according to Chen (2016) and Gao, et al. (2017), is as follows:

Forget gate (determine the information to be deleted from the cell state):

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

Input gate (update the old cell state):

$$\hat{C}_t = tanh\ (W_c[h_{t-1}, x_t] + b_c) \tag{2}$$

$$U_t = \sigma(W_u[h_{t-1}, x_t] + b_u) \tag{3}$$

$$C_t = f_t * C_{t-1} + U_t * \hat{C}_t \tag{4}$$

Output gate (filter the cell state that is going to output):

$$O_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = O_t * tanh\ (C_t) \tag{6}$$

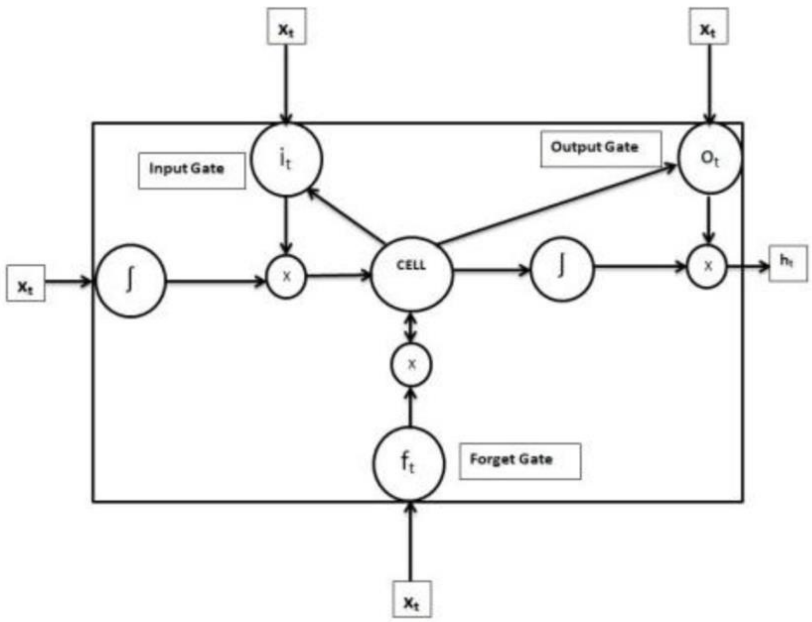

Figure 3: Long Short-Term Memory model

Figure 3 shows the flow of data through the standard LSTM model. x_t represents the vector of inputs, h_t represents the vector of outputs, the cell saves the state, i_t represents the vector of the input gate, f_t represents the vector of the forgotten gate, o_t represents the vector of the output gate. W_c, W_f, W_o, W_u and U_t are weights. b_f, b_c, b_u, b_o are shift vectors. *Source: Panday, et al. (2020).*

The figure demonstrates the LSTM model as illustrated by Panday, et al. (2020). x_t represents the input vector, h_t represents the output vector, the cell saves the state, i_t represents the input gate vector, f_t represents the forgotten gate vector, o_t represents the output gate vector. W_c, W_f, W_o, W_u, and U_t are weights. b_f, b_c, b_u, b_o are shift vectors. We use the past closing prices of the stocks, which include the S&P 500 index and the company stocks, as an input vector.

For an in-depth explanation of the functioning of the LSTM model, see Hochreiter & Schmidhuber (1997). In the following, we will illustrate only the elementary steps followed and fundamental settings of the model used for running our analysis. As in any neural network model, we must normalize the input data first, by rescaling it to the range of the activation function, so that the value range of the inputs are uniform. The value is scaled to the interval of [-1, 1] since the default activation function for is a sigmoid function with the range from -1 to 1. Accordingly, we will have to conduct a corresponding inverse-transform to get the forecast values back to the original scale after we obtain the prediction values. Then, by setting the "stateful" argument to TRUE, we can get the internal states after processing one input layer as the initial states for the adjacent layer. Before compiling the LSTM neural network, we have to convert the input from a time-series data into a supervised sequence, with a 3-dimensional array. The 3-dimensional array for the reshape of the input batch are samples, time steps and the features. The samples, also called batch size, are the number of observations in each layer and it is typically set to 1. Time step means the separate time steps for a given observation. Due to the limitation of data length, this research makes predictions with the time step set to 1. The feature is set to 1 since our research is a univariate case. According to these three settings, we reshape the input X into a three-dimensional array with 1 sample, 1 time steps, and 1 feature at every time step. After defining the model, the next step is to fit it. When fitting the LSTM, we set the "shuffle" argument to FALSE to avoid shuffling the training data and maintain the dependencies between the inputs. Model parameters are trained on 50 epochs. We run a loop over the epochs, where with each epoch, we fit the model and reset the state through the argument of "reset_state". Then, we can make predictions based on the fitted model and plot the results.

The S-LSTM proposed in this thesis functions essentially the same way the LSTM model does, with the addition of the sentiment scores obtained in the first step of our analysis. The binary sentiment scores are incorporated into the LSTM model in the form of one input vector composed of the values which range from -1 to +1, in addition to the daily historical stock prices, which make up the second input vector. We thus apply the LSTM neural network in two distinct ways depending on the input vectors and obtain the forecasting result for the LSTM and S-LSTM separately.

4. Analysis

4.1 Sentiment analysis

The first stage of our experiment consists of sentiment analysis. There is much research applying different methods to investigate sentiments and their character traits, as well as assigning sentiment scores to the text. As introduced above, sentiment analysis consists of a matching process of keywords and phrases from the text in question with existing or personalized dictionaries (Samuel, et al., 2020). Although there are variations of such dictionaries, most appear to have overall relatively similar content. In this thesis, we chose to conduct our sentiment analysis using Twitter data with two packages in R, namely the “Syuzhet” and “tidytext”, to evaluate the tweets. This decision was based on the following reasons. The “Syuzhet” package would allow us to grasp different tones of the tweets as well as how the different emotions balanced out and give us a general understanding of the overall Twitter accounts’ performance during the pandemic. The “tidytext” package could assign tweets positive and negative sentiment scores which could then be used as input for stock prediction models.

The sentiment analysis is conducted for the entire period between March 1 and April 29, 2021. Our sentiment analysis follows the two common complementary approaches, binary and emotion detection. Using the “tidytext” package in R, we obtain an output for binary sentiment classification. This package contains various dictionaries of words, and every word is scored by positive or negative connotations. We can get an impression of whether the statements in tweets are generally positive or negative, as the package allows us to compare each individual word in the tweets against the lexicon. The sentiment of the entire sentence can be derived from the sentiment score of each word. By rounding the time of each tweet into the nearest date, we can get the average COVID-related sentiment score on Twitter for each day. In addition to the binary sentiment analysis, we implement the emotion detection approach to learn the overall emotion structure and check if there is any specific emotion that stands out during the period. The R package “Syuzhet” enables us to grasp the tone of the tweets by breaking the emotions contained in the text into ten different categories and scoring the emotions on each tweet. The sentiment categorization is based on Plutchik’s wheel of emotions, which consists of four pairs of emotions; trust and disgust, joy and sadness, surprise and anticipation, and fear and anger (Xue, et al., 2020a). In addition, it also returns a score of negative and positive emotions. We chose to incorporate both approaches into our sentiment analysis as they provided us with complementary data helpful for better comprehending public opinion, by producing both a broader perspective of the overall direction of sentiment and more in-depth data on the specific emotions. This is particularly useful in comparing dominant emotions with other stages of the pandemic. However, the progression of single emotion sentiment will not be studied and applied in the stock price forecasting models, since based on the results, the most dominant emotions of trust and fear do not present a significant difference from the remainder of the emotions. The fear sentiment, in particular, had been proven to be the one that is most closely associated with the spread of coronavirus (Samuel, et al. 2020). Since we did not observe such a difference based on our data, we will not further track the sentiment for those emotions. Hence, in our research, only the binary sentiment score will be used to adjust the LSTM model in the following.

Both sentiment analysis approaches include the following steps, according to Samuel, et al. (2020), R for Journalists (2019) and Van den Rul (2019). First, we split the tweets under the "text" column into individual words and form a data frame where each word represents a new row. Then, we merge the data frame of each tweet's words with the lexicon and remove the unmatching words. These unmatching words may, for instance, include hashtags or certain symbols. To detect emotions in the tweets, we apply the function "get_nrc_sentiment", which calls on a sentiment dictionary, the so-called NRC dictionary, to investigate which emotions were present in a text file, and to what degree. Then, we can plot the total sentiment for different emotions. Binary sentiment scores, on the other hand, are created using the "get_sentiment" function where the individual words are compared against the lexicon to be assigned a positive or negative sentiment score. Finally, we merge the sentiment scores for each word and get the mean net sentiment score for each day. The result of the average sentiment can be plotted into a chart. For the sentiment scores obtained from the emotion detection analysis, higher values represent more intense prevalence of the different emotions. For the scores obtained from the binary approach, values above zero represent positive sentiment, whereas values below zero depict negative sentiment. The results of the sentiment analysis are shown in Figure 3 and Figure 4, respectively.

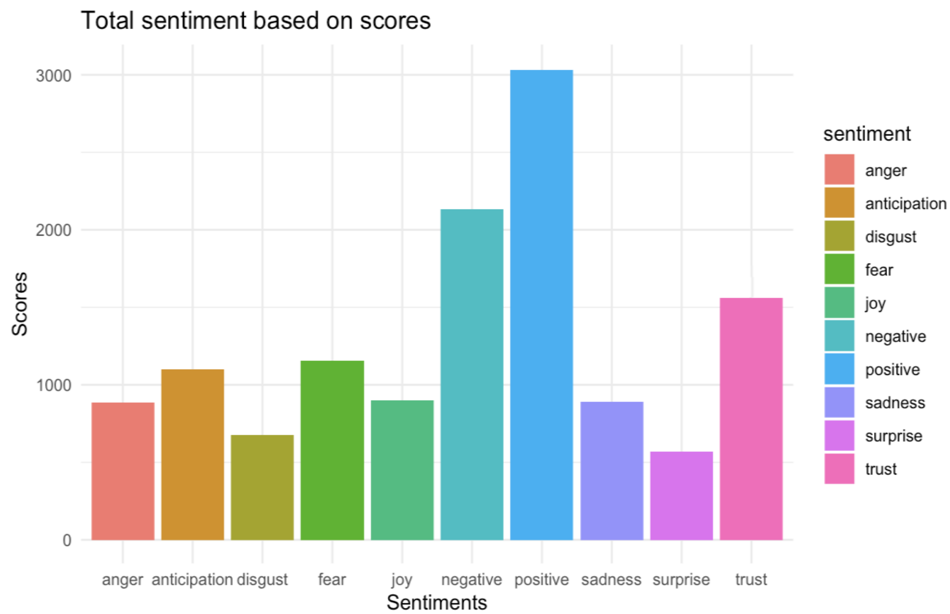

Figure 4: Result of the emotion detection approach to sentiment analysis of COVID-19-related tweets

Figure 4 shows that sentiment obtained from Twitter in the US between March 1 and April 29, 2021 is overall more positive than negative. The most dominant emotions detected were trust, fear, and anticipation. *Source: Twitter data processed in R.*

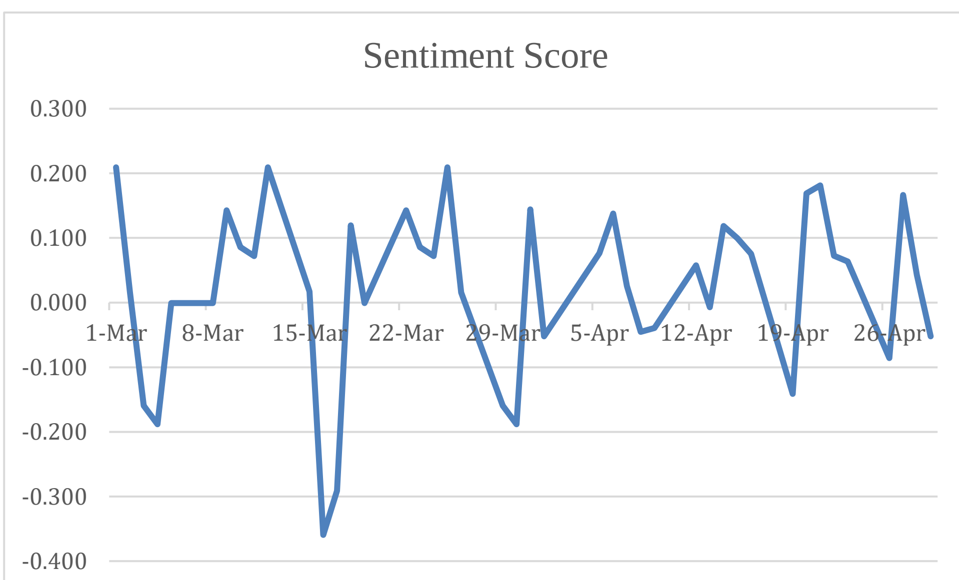

Figure 5: Results of the binary approach to sentiment analysis of COVID-19-related tweets

Figure 5 shows that sentiment on Twitter in the US between March 1 and April 29, 2021 is overall positive. *Source: Twitter data processed in R.*

Based on the visualization of the emotion detection analysis, we find that trust is the dominant emotion in tweets, followed by fear and anticipation, and that the general positive attitude outweighs the negative one. The binary sentiment analysis of the Twitter data shows that the average sentiment score is positive most of the time during the period in question, indicating that most of the users on Twitter are holding a positive attitude towards the COVID-19 pandemic situation at this stage of the pandemic.

We then normalize the obtained sentiment score, as recommended in research conducted by Xia & Chen (2021), since existing approaches trained on regular Twitter data tend to generate a positive average score. This might be because a majority of Twitter users have a positive attitude towards the pandemic or due to some intrinsic limitation of the sentiment analysis models and the bias of the data retrieved from Twitter. In addition, we also consider the tweets' volume impact on the sentiment analysis. Hence, we normalize the obtained sentiment scores by applying the formula of $S_i = S_i - \underline{S}$ (where S_i is the daily binary sentiment score and the $\underline{S}$ is the average binary sentiment score) before using the sentiment scores to compare with and predict stock prices. This is necessary to better justify the research and reduce bias in the result (Xia & Chen, 2021). We then proceed to the second stage of our experiment, the incorporation of the obtained sentiment scores into the LSTM model for stock market prediction.

4.2 Implementation of stock prediction models

We, thus, now turn our attention to the financial data obtained from Yahoo Finance. The data are divided into training data and test data, where the former provides the basis for learning the pattern for the dynamic of the stock price time series and the latter is used to make predictions for stock prices. The split of the data is set at the date April 9th, 2021, which means that the training set takes up a proportion of 70% and the test set takes up 30%. Since our database is not large, it is unnecessary to split it into non-meaningful datasets. The proportion is chosen according to the similar research that has been done in the past, such as Panday, et al (2020).

We then proceed with the execution of our analysis using a variation of the LSTM model which incorporates binary sentiment scores, as introduced above. To estimate the accuracy of the S-LSTM model, we run it together with the other predicting models, ARIMA and traditional LSTM, and then compare the results. As explained, the input data for the three comparison models is the time series of stock prices, while the input for the S-LSTM is the time series of stock prices and the time series of sentiment data obtained from the COVID-19 sentiment analysis on Twitter. The data that is put into the different models is shown in Table 2 below. R is the stock price dataset which consists of both the eleven different companies' stock prices and the price of the S&P 500 index. S refers to the binary sentiment scores generated from the Twitter data. These input vectors will be sent to the ARIMA model and LSTM neural networks for stock price forecasts.

Model	**ARIMA**	**LSTM**	**S-LSTM**
Input Data	R	R	S+R

Table 2: Model names and input vectors used in our analysis

Table 2 shows the input vectors used for the different models, where R is the stock price data set which includes both company stock prices and the prices of the S&P 500 index, while S is the binary sentiment score obtained from the Twitter sentiment analysis. *Source: Own elaboration.*

4.3 Results

The results of the predictions for the price of the S&P 500 index are shown in Figures 6, 7 and 8 below. Comparing the performance of the different models, it can be seen from the charts that the difference between the predicted and observed value is smaller for the LSTM models, which proves that the LSTM can predict the next day closing value more accurately than the ARIMA model. The forecast of the ARIMA model shows a straight line. This is since the ARIMA forecasting model tends to be mean reverting. The ARIMA model's forecast tends to follow the mean because the model cannot capture the random events that occur in a particular period. This confirms our decision of choosing the LSTM model as a basis for incorporating our sentiment measure. Furthermore, we detect that the forecasted values using the S-LSTM proposed in our analysis almost perfectly match the observed values. This shows that including sentiment into the existing model increases its accuracy in predicting the S&P 500 index, although not as considerably as we expected.

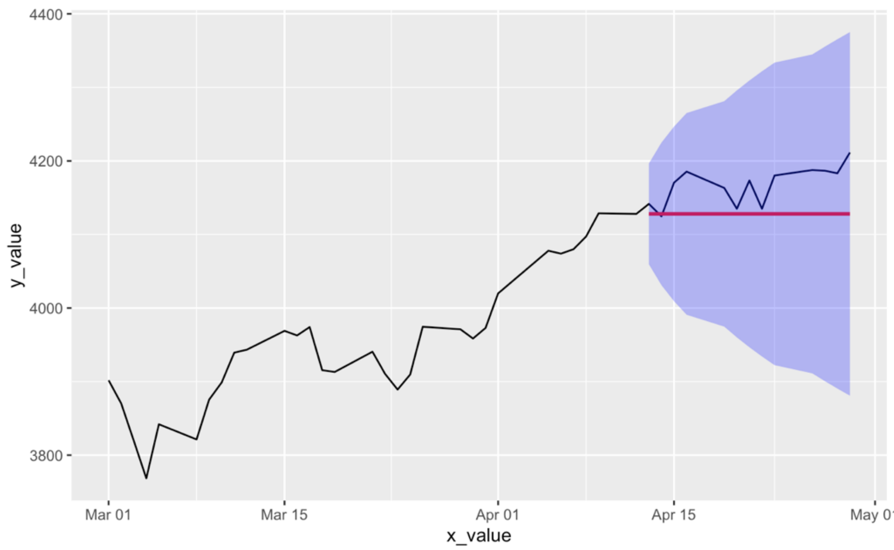

Figure 6: Performance of the ARIMA model in forecasting the S&P 500 index

Figure 6 depicts a comparison of the forecast result of the ARIMA model (shown by the red line) and the observed closing prices of S&P 500 (shown by the black line). The blue region represents the confidence interval which is between (-1.96, +1.96), where 95% of the region of a normal distribution falls within 1.96 standard deviations of the mean. *Source: Yahoo Finance data processed in R.*

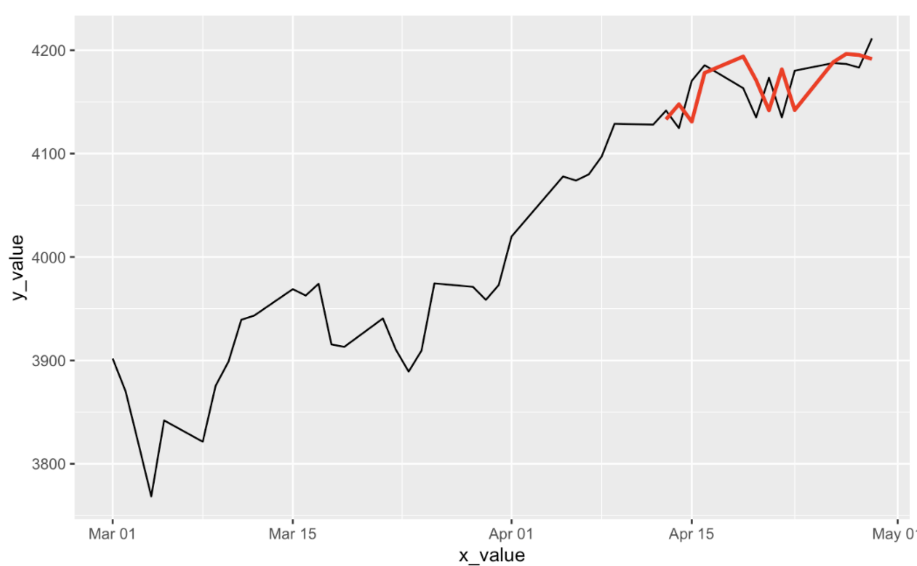

Figure 7: Performance of the LSTM model in forecasting the S&P 500 index

Figure 7 shows a comparison of the forecast result of the LSTM model (shown by the red line) and the observed closing prices of S&P 500 (shown by the black line). *Source: Yahoo Finance data processed in R.*

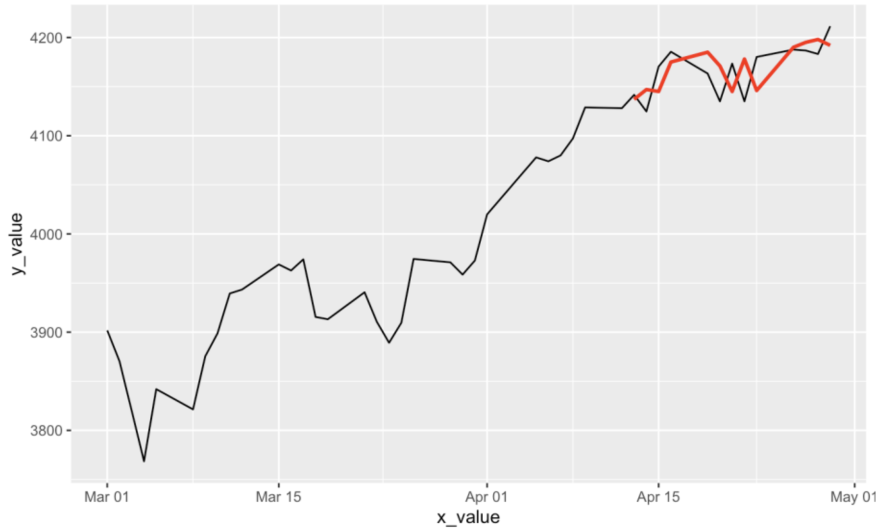

Figure 8: Performance of the S-LSTM model in forecasting the S&P 500 index

Figure 8 depicts a comparison of the forecast result of the S-LSTM model (shown by the red line) and the observed closing prices of S&P 500 (shown by the black line). *Source: Yahoo Finance data processed in R.*

To quantitatively evaluate the models for robustness, we use two statistical gauges of precision, the mean absolute error (MAE) as well as the root mean square error (RMSE). The formulas for the two ratios are listed below:

The formula for calculating the MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - ty_i| \tag{7}$$

where $\hat{y}_i$ is the predicted and y_i is the observed value. The lower the value of MAE, the higher the prediction accuracy.

The formula for computing the RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{8}$$

where $\hat{y}_i$ is the predicted and y_i is the observed value. The lower the value of RMSE, the higher the forecasting accuracy.

The closer the calculated value of MAE and RMSE is to 0, the smaller the difference between the predicted and observed value and thus, the greater the prediction precision.

The formula for the MAE and RMSE ratio improvement calculation is as follows (Ko & Chang, 2021):

$$MAE_{Impr.} = \frac{MAE_{LSTM} - MAE_{S-LSTM}}{MAE_{LSTM}} \quad (9)$$

$$RMSE_{Impr.} = \frac{RMSE_{LSTM} - RMSE_{S-LSTM}}{RMSE_{LSTM}} \quad (10)$$

The results of the different models for predicting the S&P 500 index are shown in Table 3. We can observe that when applying the S-LSTM model utilizing sentiment analysis results based on COVID-related tweets, the MAE and RMSE value can be reduced. However, the non-adjusted traditional LSTM model appears to be only slightly less accurate than the S-LSTM approach. According to our results, the MAE of our S-LSTM model shows a 4.572% improvement in accuracy when compared to the baseline LSTM model, while the RMSE shows an improvement in accuracy of 5.769%. Both LSTM models appear to be considerably more accurate in their forecasting ability than the ARIMA model.

Model	**ARIMA**	**LSTM**	**S-LSTM**
MAE	40.05308	22.90407	21.85689
$RMSE$	46.77925	26.99959	25.44187

Table 3: Accuracy metrics of the different models for forecasting the S&P 500 index

Table 3 shows that the S-LSTM model obtains the relatively lowest MAE and RMSE values of predicted stock prices and observed closing prices, making it the most accurate of the three approaches. However, the conventional LSTM model is only slightly less accurate. *Source: Own elaboration.*

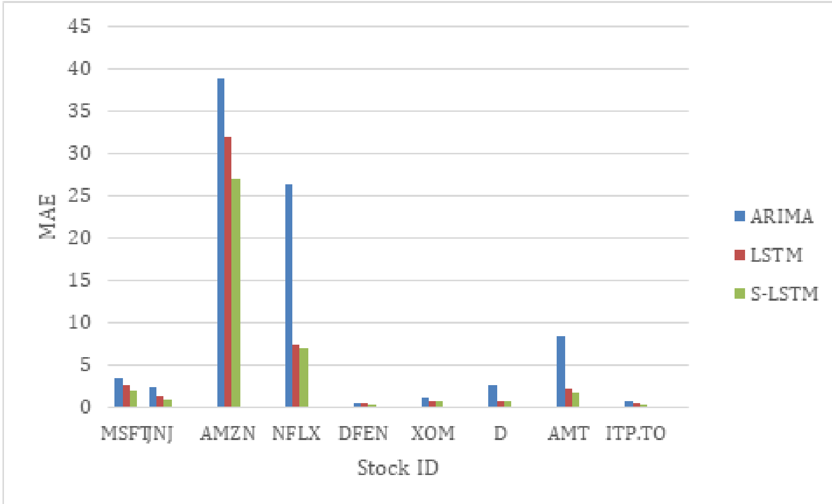

Figure 9: MAE of the different models' accuracy in forecasting the prices of the stocks from the 11 sectors

Figure 9 depicts a comparison of the MAE ratio results for the prediction of stock prices of representative stocks from the different industries the S&P 500 is composed of, using the ARIMA, LSTM and S-LSTM models. The ARIMA model appears to be least accurate overall. All three models are least accurate in predicting the future prices of stocks from the consumer discretionary, communication services and real estate sectors, respectively. Still, S-LSTM is most accurate overall, closely followed by the conventional LSTM model. *Source: Yahoo Finance data processed in R.*

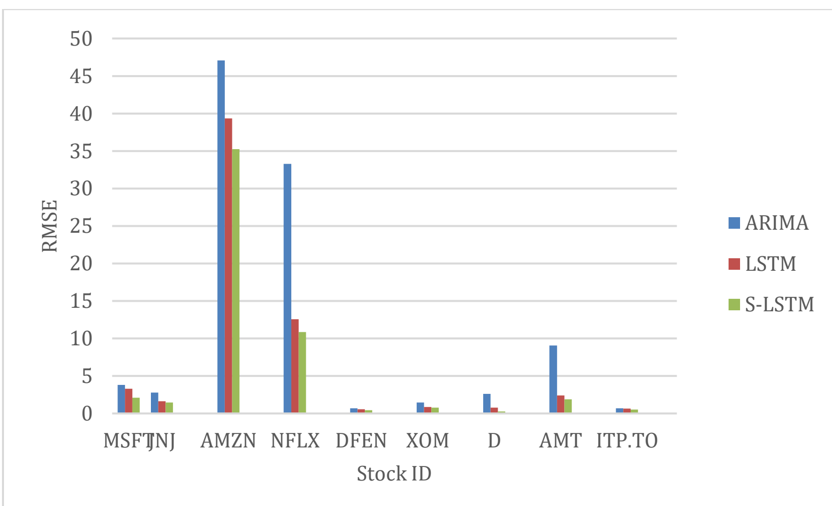

Figure 10: RMSE of the different models' accuracy in forecasting the prices of the stocks from the 11 sectors

Figure 10 shows a comparison of the RMSE ratio results for the prediction of stock prices of representative stocks from the different industries the S&P 500 is composed of, using the ARIMA, LSTM and S-LSTM models. The ARIMA model appears to be least accurate overall. All three models are least accurate in predicting the future prices of stocks from the consumer discretionary, communication services and real estate sectors, respectively. Still, S-LSTM is most accurate overall, closely followed by the conventional LSTM model. *Source: Yahoo Finance data processed in R.*

As shown in Figure 9 and 10 above and Tables 4-6 in the appendix, the performance improvement of forecasting the prices of different stocks using the different methods varies. Across all the sectors analyzed, the experimental results have an improvement for the two ratios. Adopting the adjusted S-LSTM model improves the MAE and RMSE ratio for all the selected company stocks with an average improvement ratio of 19.487% and 23.738% respectively, which is in accordance with the result from the experiment conducted by Ko & Chang, 2021. The improvement is more statistically significant for two companies, Johnson & Johnson (JNJ) and Aerospace & Defense (AMT), which are within the sectors of Healthcare and Industrial, respectively. Healthcare consists of medical supply and pharmaceutical companies and similar science-related operations. The Industrial sector consists of a broad spectrum of companies, including, for instance, from airline as well as railroad companies. Aerospace & Defense and Construction & Engineering are among the principal subsectors. For such companies, it appears that one would achieve better stock price predictions when taking the COVID-19 sentiment into consideration.

Overall, based on the results, it appears that the S-LSTM model outperforms the other prediction models, which means the sentiment factor improves the accuracy of the traditional LSTM model. Our results thus confirm our initial hypothesis. However, the overall precision of the S-LSTM model is only slightly higher than that of the base LSTM model.

5. Discussion

5.1 Interpretation of results

In our analysis, we combined the LSTM neural network with text sentiment analysis over a period of two months to investigate the impact of the COVID-19 sentiment from Twitter on stock prices in the US. Our findings show that the accuracy of the LSTM stock price prediction model improves, although only slightly, with the addition of pandemic sentiment data. In an environment where communication technologies and social media are highly developed, Twitter sentiment has the potential to display a genuine reflection of, as well as having a profound impact on the macroenvironment, making it a possibly significant and reliable source for stock price prediction models. Based on our quantitative analysis, the COVID-19-related Twitter textual content appears to succeed in capturing emotions of the users and is easily transformed into sentiment factors that can then be combined with the LSTM model. According to the results, the COVID-19 sentiment on Twitter is therefore a helpful indicator for stock prices which, to a certain degree, improves the accuracy of the prediction models without adding too much complexity. This finding confirms our hypothesis, although the improvement in precision was rather marginal, pointing to a weaker impact of sentiment on prices than we had expected. In the following, we will discuss our findings more in depth, explore their implications and point out limitations of our analysis.

With both steps of our analysis, we were able to provide certain new insights, adding onto existing research. Our sentiment analysis served to detect the public attitude and emotions towards COVID-19 in the later stages of the pandemic. The results of our sentiment analysis thus provide an updated depiction of sentiment, as public opinion has evolved substantially along with pandemic developments and government responses during the same period. Overall, the sentiment detected in our analysis appeared to be in line with similar analyses conducted at earlier points in time. The overall more positive sentiment as well as the dominant emotions of trust and fear are findings similar to those detected previously by other researchers, as has been explored in the literature review. The principal difference of our results to findings from previous analyses is the fact that although trust and fear were usually among the most dominant emotions detected, it appears that these two have now switched places. In earlier stages of the pandemic, fear had been detected to be more dominant than any positive emotions in several studies. According to our results, it seems that trust has taken over this position, pushing fear to the second place. This change signals that there has been positive progress in the public perception of the pandemic.

The prevalence of pandemic-related trust might be linked to the overall optimism and hope that also seem to be reflected in the stock market. Another reason might be the increase in trust in the government response and handling of the pandemic, which is proving itself to yield good results. The public's trust might also be related to the US healthcare system, which has proven to handle both the pandemic and the rollout of vaccinations effectively, particularly under the new administration. In turn, fear of the pandemic had been the clear most dominant emotion in the early months and was particularly related to the unknown nature of the disease and the uncertainty created by this. Possible interpretations of fear over a year later might be more linked to the pandemic response. Particularly, fear that the vaccine rollout does not proceed as expected, or that the vaccine is not as effective or safe as expected, might be prevalent. Another possible reason for fear might be that the loosening of restrictions could lead to another surge in new cases. Fear might also be caused by the threat of new virus variants and the possibility that the vaccine might not protect as well against these. Essentially, the major, most likely origins of fear thus appear to be the same reasons that other individuals base their trust on. As these aspects are two sides of the same coin, whether they trigger feelings of trust or fear appears to depend on a person's interpretation. According to our results, during March and April of 2021, more individuals might therefore have interpreted these facts as cause for trust than for fear.

The overall more positive than negative sentiment might be related to the detected emotions, specifically the fact that trust outweighed fear, given the hopeful developments of the pandemic over the past months in the US. In early 2021, the COVID-19 death rate declined. After reaching a peak in September of the previous year, both the hospitalization rate and newly reported cases saw a significant reduction and remained at a relatively stable level during March and April, with less than 50,000 cases and about 60,000 respectively (Allen, 2021). In the first week of March, several states made an announcement of loosening restrictions implemented since the outbreak of the pandemic, for instance regarding the wearing of masks (Fitzsimons, 2021). In addition, vaccines are being rapidly distributed, achieving the 200 million goal set by the president (Murphy, 2021). Businesses are also preparing to reopen in many states (Fitzsimons, 2021). All these factors could help to explain the overall positive COVID-related sentiment on Twitter. As explored in the literature, the positive developments of the stock market during the last months have also been linked to these factors. However, this stock market trend might also reflect an overreliance on optimism, which could make the stock market poised for another downturn if reality does not fulfill expectations.

By including the binary sentiment score into a stock market prediction model, we then built on existing research. We added a new layer with an analysis conducted against the backdrop of the pandemic and found that incorporating sentiment towards the pandemic into the LSTM model slightly improved its accuracy in forecasting future stock prices. This was detected by applying our refined S-LSTM model for predicting the price of the S&P 500 index, finding that it was considerably more accurate than the ARIMA model and slightly more accurate than the conventional LSTM model in forecasting the index. Generally, this might indicate that sentiment towards COVID-19 does impact investment behavior, implying that investment decisions are not taken on the basis of fully rational information only. Particularly, our findings imply that individuals appear to assign an irrationally high value to not only actual pandemic developments, but also their thoughts and feelings about it, even for making decisions in seemingly unrelated areas, such as the stock market.

We furthermore applied the S-LSTM model for forecasting the prices of one stock from each of the eleven sectors that make up the S&P 500 index. We found that our approach performed better than the standard LSTM model and significantly better than the ARIMA model. Overall, the fact that our S-LSTM approach proved to be more accurate in forecasting stock prices implies that these prices might, in fact, be influenced by pandemic sentiment, as this was the only change made to the model. As mentioned previously, LSTM neural networks are one type of deep learning approach, which may not be sufficient to work on their own to analyze and make predictions of the time series data, such as stock prices. We conducted our analysis based on the assumption that those models based on the traditional LSTM approach that combine a certain number of additional factor inputs have the potential to increase the accuracy of prediction since it has been tailored to fit the current changing market environment. Combining the conventional model with sentiment analysis to create a S-LSTM model appeared to be an interesting manner of improving its accuracy. However, we were rather surprised to find that our addition to the model did improve it, but not as significantly as expected. This finding could be interpreted in several different ways. One interpretation would be that the existing LSTM model is already very accurate on its own, leaving little room for improvements and thereby explaining the only marginal increase in precision. However, it could also mean that sentiment towards the pandemic might not be as impactful on stock prices as expected, partially refuting our initial assumption of this relationship. Taking this one step further, another interpretation could be that sentiment generally might not be as relevant for stock prices as we had assumed. This could point to investors being more rational than expected, as sentiment might not impact individuals' investment behavior as strongly as we had supposed. This line of argumentation would thus hold that our results show that financial markets, or at least the S&P 500 index, are more efficient than expected. However, given existing findings on the impact of overall sentiment on prices makes this interpretation seem unlikely. A fourth interpretation concerns potential issues with our methodology or choice of Twitter as a sentiment data source, which might not be ideal for the purpose of this analysis. The limitations of our approach are explored more in-depth in section 5.3.

Interestingly, another finding from our analysis was that there appeared to be differences in the forecasting accuracy for the different stocks from the eleven sectors. An overview of the accuracy metrics for the eleven stocks can be found in Table 4-6 in the appendix. The prices of stocks from consumer discretionary and communication services were forecast least accurately by all three approaches, including our S-LSTM model. Particularly the communication services and real estate stocks saw stark differences in accuracy between the models. Although not highly accurate in predicting the prices of these stocks, our approach still performed better than the other two, especially for the consumer discretionary stock. There might be several reasons that explain why these stocks appear to be more difficult to forecast overall, such as industry-specific external factors like the particularly strong impact of economic or political developments, certain industry trends or even firm-specific characteristics of the stocks selected for our analysis. The fact that our approach seemed to forecast their prices more accurately than the other approaches implies, however, that sentiment towards the pandemic might be an important factor affecting prices as well, which is not captured by other models.

A possible explanation for the inaccuracy of our approach in forecasting particularly the consumer discretionary stock might be related to the fact that the pandemic has had a weaker overall impact on its price. Based on existing studies of the pandemic, although individuals' lifestyles and investing behaviors have been changed greatly by the pandemic, consumption demand tends to remain at approximately the same level, as consumption or investment is often simply postponed or switched to other accesses. The postponed consumption and investment can even be followed by a rebound when the pandemic recovers, but this remains to be seen in the future. Notwithstanding, the S-LSTM model was considerably more precise in predicting the price of this stock than both other approaches. This could indicate that although the pandemic itself might have had a weaker effect on this stock, sentiment towards the pandemic might have impacted its price considerably. Further research considering more than only one stock from this industry is needed, however, to confirm this finding.

We found that our approach, incorporating pandemic sentiment, appeared to be most successful in accurately forecasting the price of an energy stock, ExxonMobil, an oil and gas company. This might be connected to the overall global impact of the pandemic on transportation, particularly due to lockdowns as well as the move towards online communications. Rather than containing new information affecting the fundamental value of their stocks, public sentiment towards the pandemic might misestimate the impact of current and potential future pandemic developments on energy companies, which might influence prices. Our analysis, furthermore, showed that also the healthcare sector stock's price was predicted more accurately. This seems logical considering the strong connection between the healthcare sector and the pandemic. The fact that not only the pandemic itself, but also sentiment towards the pandemic help in explaining the prices of such companies might imply that COVID-19's impact on healthcare companies' stock prices is not entirely driven by fundamental new information about these companies that is not yet reflected in their price, but also by psychological influences such as sentiment. According to our results, this might be true also for those companies that develop vaccines, such as Johnson & Johnson, our example stock from this sector, although of course, one stock is not representative for an entire sector. Similarly, the fact that our S-LSTM model was more accurate in predicting the price of the industrial stock, an index of stocks from the aerospace and defense industry, is not surprising, given the strong effect the pandemic has been having on aerospace companies, such as airlines, and the often-important emotional component of opinions about defense companies, especially during uncertain times. It therefore seems natural that sentiment regarding COVID-19, particularly due to emotions like trust and fear, might influence the prices of such stocks. However, this result's representativeness for the industrial sector seems even more questionable, given the unique nature of this stock.

The improvements in prediction accuracy of our suggested approach in the other industry sectors are relatively smaller, which may be because the influence of the COVID-19 on those industries is limited to some extent, or because pandemic sentiment did not impact their prices as much. Therefore, the incorporation of a measure of sentiment towards the pandemic does not allow the model to capture those factors most impacting these stocks' prices.

Overall, the approach proposed in this thesis achieved a slightly higher forecasting accuracy than existing models in predicting the S&P 500 index as well as the prices of stocks from all different sectors. Our results are, thus, generally in line with existing research on the topic. Particularly the findings from our sentiment analysis match other researchers' results very well, implying that overall sentiment during the pandemic is rather similar to sentiment towards the pandemic and has developed rather gradually over time, slowly progressing from more negative, fear-based sentiment towards a more hopeful, trust-based sentiment. Furthermore, we were able to confirm the value of including a sentiment variable into an existing stock price prediction model. However, the improvement in precision achieved by our approach appears to overall be less significant than the results obtained by other researchers, such as Chou et al. (2021), who have incorporated both overall sentiment and attention measures into such models. Our findings, furthermore, extend the work of Jabeen, et al. (2021), who detected that sentiment towards the pandemic impacted the prices of stocks from those industries most affected by pandemic. Our results suggest that pandemic sentiment appears to not only impact those stocks, but also the market as a whole, as measured by the S&P 500 as well as stocks from all sectors, although to a varying degree.

Thus, a key contribution our research is able to make to extend the existing body of literature is that, according to our findings, sentiment towards the pandemic appears to impact stock prices even over a year after the outbreak of the pandemic. This is particularly interesting as it demonstrates both the long lasting repercussions of the pandemic on public opinion and suggests that stock prices are vulnerable to sentiment towards events for an extended period of time. Specifically, our findings imply that prices are affected even by sentiment towards subsequent developments of an event rather than reacting only initially. There can be a number of reasons for such a durable effect. In the case of this pandemic, it might, in part, be connected to the large number of individuals who have started to invest in the stock market during the pandemic, as these often rather unsophisticated individuals might make investment decisions that are even more influenced by sentiment, and particularly by positive attitudes towards future pandemic developments. Overall, this finding might prove useful when analyzing sentiment towards different kinds of events, as it suggests that the emotions caused by an event within one area can have repercussions on behaviors in different areas as well.

5.2 Implications

Our findings, although not suggesting as strong an impact of pandemic sentiment on the stock market as we suspected, thus do provide certain new insights. These have several implications for different parties. Researchers might benefit from our results, as they provide an initial indication of the value of incorporating sentiment towards a certain phenomenon or development that is both highly impactful and long lasting into existing stock price prediction models, such as the LSTM model. Our findings might thus motivate other researchers to further investigate this approach, particularly to assess whether a better measure of sentiment towards a phenomenon like the pandemic, or the adjustment of any of the other variables, such as duration, would improve existing approaches more significantly.

We consider, however, that the main contribution of this thesis is to provide a refined approach to stock price forecasting for professional investors, investment managers and generally those parties that hold a stake in the movements of stock prices. Following our approach for stock price prediction can help investors make more informed investment decisions. Including our approach into existing analyses or approaches will allow them to adjust their asset allocation accordingly in order to increase profitability (Chou et al., 2021). Naturally, the approach likely needs to be further refined and adjusted to increase the feasibility and value of applying it for making investment decisions. Our approach is thus useful most directly for professional investors, such as institutions.

This, in turn, can also indirectly benefit society through the potentially more profitable investment of, for instance, pension funds. Members of the society might furthermore be interested in our findings to better understand how public opinion has developed along with the pandemic, as well as its impact on the stock market. Our exact approach of incorporating such sentiment into a deep-learning stock price forecasting model is likely not feasible, and potentially also not sufficiently rewarding, for private investors. However, paying attention to a rather qualitative impression of sentiment and awareness of its effect might still prove valuable for retail investors. On a related note, an important aspect is the potential link of sentiment to the emergence of bubbles. Particularly, the clear dominance of trust found in our sentiment analysis coupled with the quick rebound of the stock market after the outbreak of the pandemic and its continuing bull market state might reveal themselves to be concerning, if too heavily dependent on optimism and potentially unwarranted trust. Members of the society might therefore want to use these findings to take a cautious approach to investing in order to not suffer the disastrous repercussions of a bubble. Additionally, more precise stock price forecasting would allow for an improvement of regulatory response, thereby increasing the overall stability of the financial market and thus benefiting the society at large (Chou et al., 2021).

5.3 Limitations and suggestions for future research

Nonetheless, our approach has a number of limitations, both with regards to our choice of sentiment data source and our methodology. Using a social media source to extract sentiment comes with several drawbacks, particularly with regards to the interpretation and reliability of the sentiment data. The principal issue in this regard concerns the relationship between Twitter sentiment and the stock market. The Twitter sentiment score aims to measure the sentiment of the broader public, in this case in the US. However, not all Twitter users in the US are investors. Similarly, it stands to reason that not all investors might express their opinions or emotions on Twitter. Thus, there likely is a mismatch that complicates the approaches that connect Twitter sentiment and stock market data. Nonetheless, this mismatch is also present in other measures of sentiment and is thus not limited to only our approach. A related limitation is the fact that Twitter sentiment likely captures only individuals' sentiment, disregarding institutional investors (Hiew et al., 2019). This points to a larger discussion, however, as it is often assumed that sentiment only affects individuals' investing behavior. Yet, given the oftentimes rather low relative amount and impact of trades made by individuals when compared to institutional investors, it seems likely that if an impact of sentiment on the stock market can be observed at all, then sentiment likely impacts not only retail investors, but institutions as well. Moreover, investment managers working for institutions also tend to use social media, while often additionally having a large reach. Thus, the sentiment of investment decision makers might be captured by our approach at least to a certain extent after all. Moreover, as our analysis was limited geographically to the United States, its representativeness and applicability for other countries is also likely limited to a certain extent, given the cultural component in sentiment as well as other country-specific characteristics.

In addition to the above, there are potential incentive issues with statements and opinions shared on social media. The representativity and truthfulness of statements published on such platforms stands in contrast with potential ulterior motives for publishing them (Chen, et al., 2014). This may negatively impact the authenticity of sentiment from Twitter. A related key issue also concerns the prevalence of fake news on social media (Mohan et al., 2019). All of the above might distort measured sentiment, decreasing the accuracy of our S-LSTM. A further difficulty in this type of analysis is to properly distinguish between data that reflects sentiment and data that contains information which correctly alters the fundamental value of a stock or the market, such as risk.

This issue, however, is a common one in Finance and solving it would constitute an entirely different endeavor than this thesis.

Moreover, there are certain methodological limitations, particularly in conducting the sentiment analysis through the Twitter API and R. Firstly, the number of tweets obtained from the status updates on user timelines is limited to a maximum number set by the Twitter API. Secondly, there is a potential risk that the retrieved number of tweets with commanding keywords is less than the actual required number of tweets. Thirdly, some older tweets cannot be retrieved when calling for tweets with a certain keyword. To mitigate the effect of the data collection limitation, however, we adapted multiple steps to process the raw data to ensure the data accurately reflect the general emotion on social media as well as to guarantee the reliability of our analysis of results. A related principal limitation concerns the list of keywords used to filter for tweets containing information on the sentiment towards the pandemic. Not only might this list be incomplete, but it might also miss out on those tweets including opinions and emotions that do not explicitly refer to the pandemic but do so implicitly instead. This issue is more complex to solve, as the inclusion of additional keywords for filtering tweets would not be sufficient. Further methodological limitations include the amount of data used in our analysis. Our analysis focused on a relatively short window of time and was limited to the US. Moreover, the LSTM model used in our analysis has certain limitations as well. The event sequence is of great influence on the prediction model, reducing the accuracy of results especially when an abrupt, far-reaching, and long-lasting event occurs. Thus, it would not be enough to take only the past data in the market as a benchmark. To better tailor the existing prediction models to the current market conditions and make more accurate forecasts, the introduction of other data analysis and predicting strategies are needed.

As discussed, further refinements that address one or several of these limitations would be needed to make our approach more robust. We thus suggest that further research focus on using different key inputs. Importantly, we believe that a different sentiment source, particularly an investment-focused platform like Seeking Alpha or StockTwits, might provide valuable insights into the sentiment of investors specifically, rather than gauging the sentiment of the broader public. Alternatively, using financial metrics or Google search data, for instance, might lead to a change in sentiment scores, which might have the potential to increase the accuracy of our approach. Similarly, using a closely related but different measure of human irrationality, such as attention, might also be interesting. Conducting an analysis that takes together several sentiment measures, as has been done, for instance, by Chou et al. (2021) might prove particularly valuable.

Instead of using a different source for sentiment data, it might also prove interesting to use different stock market data. This could include utilizing a different index with distinct characteristics, such as the DJIA or the NASDAQ, or even looking at a sample of individual stocks within just one or a few industries, potentially also including more small-capitalization stocks. We suspect that, given our findings in that area as well, sentiment plays a more prominent role for certain industries than for others. This might be due to the different motivations for purchasing different types of stocks, or also due to the kind of investors that largely purchase different types of stocks. Furthermore, as has been suggested in the literature and shown in our analysis, sentiment appears to affect certain companies more than others. We believe that it would be interesting to investigate whether the prices of those stocks that were most traded or mentioned during the pandemic are particularly accurately predictable using our approach, as we suspect that these are especially heavily impacted by sentiment. Naturally, an analysis conducted based on a different time period might also yield different results. We suspect that there was likely a stronger impact of sentiment earlier in the pandemic than now. However, this might also not be the case, as the strong positive attitude and trust detected currently might have just as strong an impact as fear and pessimism had in the earlier stage. Major pandemic-related developments in the future will likely also bring about stronger sentiment, potentially causing different emotions. The applicability of our approach in analyzing this would also be interesting to test.

Additionally, one could also attempt to incorporate pandemic sentiment into a different stock price prediction model. However, the LSTM model seems to be among the most accurate and advanced approaches available. Overall, we believe that the key to enhancing our research results is to obtain sufficient, reliable, and rich data, with regards to both sentiment and stock prices, to investigate the optimal selection of window size. This might also indicate how many days the effect of COVID-19 sentiment from Twitter on stock prices lasts before reversing.

6. Conclusion

This thesis set out to investigate whether sentiment towards the COVID-19 pandemic appears to impact stock prices and thus increase the accuracy of stock price forecasting. Our research confirmed our hypothesis, as we detected that our approach appeared to enhance existing models for predicting stock prices by adding a further dimension, which appears to effectively reflect investor sentiment regarding the pandemic even in later stages of the pandemic.

Specifically, in this thesis, we assessed whether pandemic sentiment, extracted from Twitter in the form of tweets, was useful for predicting stock market developments in the US between March 1, 2021 and April 29, 2021, as measured by the S&P 500 as well as one stock from each of the index's eleven sectors. Our analysis led us to two key findings. One, the dominant emotion detected in tweets referring to the COVID-19 pandemic was trust, followed by fear and anticipation. Overall, we found that there appeared to be significantly more positive than negative sentiment towards the pandemic. Two, our S-LSTM, which incorporates the pandemic sentiment scores, does appear to be approximately 5% more accurate in forecasting the price of the S&P 500 index and approximately 20% more accurate on average in predicting the prices of one stock from each of the eleven sectors analyzed than the traditional LSTM model, according to the accuracy metrics MAE and RMSE. Our model is furthermore considerably more accurate than the ARIMA model for predicting both the S&P 500 index and the prices of the stocks from each of its sectors. We found our model to display considerable differences in forecasting accuracy for the prices of stocks from different sectors. Particularly the energy, healthcare and industrials stocks appeared to be predicted most accurately by our S-LSTM approach, suggesting a strong impact of pandemic sentiment on the prices of these stocks. Overall, our findings imply that sentiment towards the pandemic does appear to shape stock prices.

Our results provide several implications for theory, practice, regulators, and society. Theorists might be interested in further exploring the applicability of our approach in future research with different characteristics or based on sentiment towards a different phenomenon as well. Practitioners within investment management as well as professional investors might be most interested in our findings, as they enable a potentially more profitable and prudent approach to capital allocation by considering the sentiment variable and its apparent impact on stock prices. As for society, our findings underline the value of the behavioral component that aggregates an often highly informative dimension to traditional explanatory approaches. Also, as our findings possibly allow for better regulation of financial markets, society might benefit from more stable financial markets.

Existing research had so far largely focused on including sentiment analysis prior to the outbreak of the pandemic. Our research centers on doing so at an unusual moment in time while analyzing specifically the value of sentiment towards the COVID-19 pandemic. Particularly, we detected that sentiment towards an impactful event of long duration, the COVID-19 pandemic, appeared to influence stock prices even during more advanced stages of the pandemic. This suggests that sentiment towards an event might have an impact on stock prices not only directly after occurring, but that even later developments related to the event might continue to shape prices. Our findings contribute to the field of Behavioral Finance, confirming the value sentiment analysis appears to have for predicting the stock market. Nonetheless, our research has certain limitations. Naturally, our measure of sentiment is imperfect, and we have relied on Twitter as our only source for sentiment data. Overall, our analysis was based on data subject to various limitations, as explored in the preceding section. We suggest that future research addresses one or several of these limitations. Particularly a larger data set is likely to provide valuable additional insights.

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Appendix

Sector	Company Name	Symbol	MAE	RMSE
Information Technology	Microsoft Corporation	MSFT	3.393843	3.81572
Health Care	Johnson & Johnson	JNJ	2.377692	2.792217
Consumer Discretionary	Amazon	AMZN	38.79537	47.06526
Communication Services	Netflix Inc.	NFLX	26.4031	33.29637
Industrials	Aerospace & Defense	DFEN	0.45923	0.6881241
Energy	Exxon Mobil	XOM	1.061538	1.460005
Utilities	Dominion Energy	D	2.476151	2.625975
Real Estate	American Tower Corp.	AMT	8.290767	9.084556
Materials	Intertape Polymer Group	ITP.TO	0.5592308	0.6989057

Table 4: Accuracy metrics of the ARIMA model in forecasting the prices of the stocks from the 11 sectors

Table 4 shows how the ARIMA model's forecasting accuracy varies considerably for the prices of stocks from different sectors. It performs best in forecasting the price of industrial and materials company stocks, while being unequivocally least accurate for the consumer discretionary stock. *Source: Own elaboration.*

Sector	Company Name	Symbol	MAE	RMSE
Information Technology	Microsoft Corporation	MSFT	2.586637	3.282945
Health Care	Johnson & Johnson	JNJ	1.269448	1.618627
Consumer Discretionary	Amazon	AMZN	32.05725	39.35979
Communication Services	Netflix Inc.	NFLX	7.315395	12.56764
Industrials	Aerospace & Defense	DFEN	0.4459215	0.5603249
Energy	Exxon Mobil	XOM	0.704185	0.8819289
Utilities	Dominion Energy	D	0.7400043	0.7919839
Real Estate	American Tower Corp.	AMT	2.127273	2.395673
Materials	Intertape Polymer Group	ITP.TO	0.5265721	0.6571308

Table 5: Accuracy metrics of the LSTM model in forecasting the prices of the stocks from the 11 sectors

Table 5 shows how the standard LSTM model's forecasting accuracy varies considerably for the prices of stocks from different sectors. It performs best in forecasting the price of industrial and materials company stocks, while being unequivocally least accurate for the consumer discretionary stock. *Source: Own elaboration.*

Sector	Company Name	Symbol	MAE	RMSE
Information Technology	Microsoft Corporation	MSFT	1.933669	2.103155
Health Care	Johnson & Johnson	JNJ	0.1299964	0.1516543
Consumer Discretionary	Amazon	AMZN	27.03412	28.26319
Communication Services	Netflix Inc.	NFLX	0.8669637	0.8684792
Industrials	Aerospace & Defense	DFEN	0.1251071	0.1253918
Energy	Exxon Mobil	XOM	0.04894603	0.05975741
Utilities	Dominion Energy	D	0.1781028	0.2711822
Real Estate	American Tower Corp.	AMT	1.801537	1.90543
Materials	Intertape Polymer Group	ITP.TO	0.3001845	0.3302888

Table 6: Accuracy metrics of the S-LSTM model in forecasting the prices of the stocks from the 11 sectors

Table 6 shows how our refined S-LSTM model's forecasting accuracy varies considerably for the prices of stocks from different sectors. It performs best in forecasting the price of energy, industrials, and healthcare company stocks, while being unequivocally least accurate for the consumer discretionary stock. *Source: Own elaboration.*