Stock Markets Performance During A Pandemic: How Contagious Is COVID-19?

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The American University in Cairo

School of Business

Stock Markets Performance During A Pandemic: How Contagious Is COVID-19?

A Thesis submitted to
Department of Management

In partial fulfillment of the requirements for the degree of
Master of Science in Finance

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Abstract

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Key words: Stock Market, Sentiment Analysis, Twitter, COVID-19, Pandemic, GARCH.

Background and Motivation: The coronavirus (“COVID-19”) pandemic, the subsequent policies and lockdowns have unarguably led to an unprecedented fluid circumstance worldwide. The panic and fluctuations in the stock markets were unparalleled. It is inarguable that real-time availability of news and social media platforms like Twitter played a vital role in driving the investors’ sentiment during such global shock.

Purpose: The purpose of this thesis is to study how the investor sentiment in relation to COVID-19 pandemic influenced stock markets globally and how stock markets globally are integrated and contagious. We analyze COVID-19 sentiment through the Twitter posts and investigate its effect on financial securities movements.

Methodology: In order to determine investor sentiment, we used text mining and Natural Language Processing (NLP) to conduct sentiment analysis on COVID-19 related tweets during the year of 2020 and got the daily polarity of those tweets. We employed a GARCH (1,1) model to study the impact of the investor sentiment, assessed by the COVID-19 related tweets, on the stock markets movements globally, in the conditional heteroscedasticity equation. The thesis uses six global stock market indices from developed markets.

Duration of the study: 4th of January 2020 - 21st of December 2020

Conclusion: Our results from the GARCH (1,1) models suggest that the investors’ sentiment based on the COVID-19 tweets shows significant impact on the conditional heteroscedasticity of the developed markets indices, indicating an impact on volatility and trading volumes of the six developed market indices.
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1. Introduction

No previous infectious disease outbreak was able to impact the global economy and global stock markets as powerfully as the Coronavirus (COVID-19) pandemic. The coronavirus outbreak, which started in Wuhan, China, in December 2019, has extraordinarily reached every corner in the world in few months. Unfortunately, millions of people have been sickened, and millions have sadly died. Early in March 2020, the World Health Organization (“WHO”) published that the virus is a worldwide health emergency and rated its global risk of spread and impact as “very high,” which is the most severe designation. Undoubtedly this designation had a similar high impact on the global economies and stock markets. Later that month, WHO declared the novel coronavirus as a global pandemic, a declaration that had a drastic adverse effect on different business sectors, economies, and subsequently global stock markets. Furthermore, the ongoing impact of COVID-19 and the need to adapt to a new normal is challenging all organizations. From a finance perspective, incorporating the uncertainty of the impact of the pandemic into the financial and economic outlook is very complex and highly judgmental.

COVID-19 unarguably had an unprecedented impact on the global economy and stock markets worldwide. It is projected that such an impact will influence the economic and financial world for years to come. Notwithstanding such economic turmoil, the research literature in relation to the effect of COVID-19 on the stock market is burgeoning. As the novel virus escalated from a regional epidemic in the Republic of China to a global pandemic, equities fell drastically, and stock markets volatility surged globally. Looking at the US markets, the first quarter of 2020 saw volatility levels that rivaled and exceeded those last seen during the Black Monday in October 1987, the financial crisis in December 2008 and the Great Depression in 1929 (Baker, 2020). Although arguably, the subsequent global policy responses to the COVID-19 pandemic provide the most persuasive explanation for its unprecedented stock market impact, it is inarguable that real-time availability of news and social media platforms like Twitter play a vital role as well.
As demonstrated in Figure 1, the major global indices presented by S&P500, Nasdaq, Dow Jones, CAC40, and DAX concurrently dropped around mid-February 2020 to hit the trough mid-March and began to rebound again by the end of March 2020. From the 14th of February till the 20th of March, the stock markets worldwide dramatically dropped down between 30-40% (with china being an exception) (Damodaran, 2020). Some analysts, including the finance guru Aswath Damodaran, believe the stock crisis started on the 14th of February. The bearish markets started to recoup slowly thanks to governments announcing relief and stimulus packages and quantitative easing actions. The drop occurred between the 14th of February, 2020 and the 20th of March, 2020 and the rise from the 20th of March, 2020 to the 1st of June, 2020. According to a Wall Street Journal’s (“WSJ”) article, the 16% drop in the Dow Jones Industrial Average on the 16th of March, 2020 marked the second-worst day in its 124-year history (Onali, 2020).
Furthermore, Figure 2 shows the Chicago Board Options Exchange’s CBOE Volatility Index (“VIX”), a popular measure of the stock market’s expectation of volatility (Brenner et al., 1989). We can notice that the VIX had two prominent peaks over the period from FY2000 till FY 2021; the first is in September 2008 during the 2008 mortgage-backed securities financial crisis. The second spike is in mid-March 2020 due to the emergence of the global pandemic COVID-19. A study by Baker & al. (2020) from the University of Chicago states that during March 2020 (more specifically from the 24th of February, 2020 to the 24th of March, 2020), there were 18 market jumps in 22 trading days (Baker et al., 2020). That surpasses any period in the past with comparative number of trading days. According to Baker et al. (2020), no other infectious disease outbreak had a similar effect on the US stock market volatility since 1985. In addition, Baker et al. (2020) argue over the last century the daily market swings were never similarly impacted by news of pandemics and infectious diseases outbreaks. He added that the 1918-1920 Spanish Flu pandemic and the influenzas pandemics of 1957-58 and 1968 did not have a similar impact (Baker et al., 2020). Such fluctuations cannot be associated with conventional microeconomic and macroeconomic factors rather behavioral finance and investor sentiment (Kumar et al., 2006).

Stock market movements are usually based on either fundamental or technical analysis evidence. The actual evidence includes but is not limited to macroeconomic indicators and microeconomic company-level specifics. Those macroeconomics indicators include growth in GDP, unemployment levels, changes in interest rates, changes in inflation rates, oil prices and other commodities prices, forex,
governmental policies (i.e., monetary policies), and market-wide risks. Behavioral finance is also a key determinant of stock market movements, as discussed in our literature. Behavioral finance includes investor sentiment. Investor sentiment is a research area in the theoretical field of behavioral finance that closely studies investors' sentiment and the way it affects stock market activity (López-Cabarcos et al., 2019). So, investor sentiment is a determinant of stock market returns. Investor sentiment is usually affected by news, events, rumors, and social media. Social media sentiment is undoubtedly a real-time indicator of investor sentiment and can be utilized as a risk factor in asset pricing frameworks as per Houlihan et al. (2017).

Our thesis studied how the investor sentiment in relation to the COVID-19 pandemic influenced stock markets globally and how stock markets globally are integrated and contagious. In other words, our thesis objective is to tackle the question of how accurately COVID-19 Twitter posts can affect and model the movement of financial securities. To determine investor sentiment, we used text mining and NLP to conduct sentiment analysis on COVID-19 related tweets and get the daily polarity of those tweets. Sentiment Analysis is the computational process of detecting, categorizing and quantifying opinions from a piece of text; in order to determine whether the writer’s attitude towards a specific topic or product is positive, negative, or neutral. In other words, it is the process of quantifying the qualitative subjects moods or sentiment into objective figures or pre-defined categories. Nowadays, sentiment analysis is widely used to help understand how people feel about a topic using NLP and news, articles, or a social media platform like Twitter. We used Twitter as it is considered a treasure trove of sentiment, especially during the COVID-19 pandemic time. People worldwide output thousands of reactions & opinions on every topic every second of every day on the Twitter platform (Cambria, 2017). Unarguably there was an abundance of misinformation and biased opinions regarding COVID-19 on social media. As such, we decided to study the tweets made by credible market-driving sources only, including the official Twitter accounts of WHO, CNN, BBC, NYTimes, DW news, and Reuters. Those Twitter accounts had the highest impact during the COVID-19 pandemic.

We consolidated all the extracted tweets by date and time in a dataset, such that we had a dataset of dates, tweets, and the source. We then conducted preprocessing on this data set. Our preprocessing included tokenization, data cleansing: Removing special characters and capital letters, removing stop words, stemming, normalization, and a syntactic Layer. The syntactic layer is used to preprocess text to simplify informal text to plain English, inflected forms of verbs and nouns are normalized, and basic sentence structure becomes explicit (Cambria, 2017).
Using the Python programming language and its tweepy library, our Twitter’s advanced search application programming interface (API) extracted 5000 tweets over the period from the 4th of January, 2020 till the 21st of December, 2020, and stored them in a dataset and a CSV file. We used the NTLK library to preprocess tweets. After data preprocessing and cleansing, we conducted a sentiment analysis on the preprocessed tweets using the text of tweets to identify each tweet’s polarity and emotional valence (i.e., positive, negative, or neutral). Later, we calculated the weighted sentiment to identify daily emotional valence each day. Thus, we had a new data set of days and the polarity of each day indicating the investor sentiment on that day.

We used the adjusted closing price for six indices that represent the developed and most liquid markets around the globe (United states, Europe and Asia). Our indices included S&P 500 representing the most extensive company stocks in different sectors and industries in the USA, and Dow Jones, Nasdaq, CAC, DAXI, and Nikkei 225. As control variables, we used the 3-months treasury yield rates for the period under study (from the 1st of January 2020 till the 21st of December 2020) and the daily 10-Year Treasury Inflation-Indexed Security. In addition, we developed six GARCH (1,1) models on the EViews statistical package for the six developed market indices; where the dependent variable is each index daily log-returns, and the independent variables are the daily polarity, we calculated out of the tweets sentiment analysis, the change in the US treasury bill daily rates and the change in the US daily inflation rates. Our GARCH (1,1) models tackled the impact of the investor sentiment, assessed by the covid-19 related tweets, on the stock markets movements globally, in both the conditional mean and the conditional heteroscedasticity equations.

Our main results from GARCH (1,1) models suggested that, while the investors sentiment based on the covid19 tweets shows no significant impact on the returns of the developed markets indices, conditional heteroscedasticity tends to be affected, indicating an impact on volatility and trading volumes of the 6 developed market indices. Our thesis builds on the previous abundant literature in behavioral finance, sentiment analysis, and text mining, and the burgeoning literature concerning the COVID-19 stock market’s impact burgeoning and literature. Accordingly, we shall proceed with reviewing previous literature to build a theoretical and empirical framework to analyze the channels of the interrelation between Covid-19 stock market impact, behavioral finance, affective computing, text mining, and sentiment analysis.
This introductory chapters serves as a brief background of our topic stating the main motivation, purpose and summarizing our thesis. The next chapter illustrates our thesis objective and hypothesis. Following that, the literature review chapter covers the theoretical framework and current knowledge of the topic. Further on, the data description and methodology are outlined in the fourth section. At a later point, the main results will be reported in the fifth section. Lastly, the paper will draw the conclusions of the thesis and suggest possible further research.
2. Literature Review


As previously mentioned, COVID-19 unarguably had an unprecedented impact on the global economy and stock markets worldwide. It is projected that such an impact will influence the economic and financial world for years to come. Notwithstanding such economic turmoil, the research literature in relation to the impact of COVID-19 on global stock markets is burgeoning.

One of the most influential papers by Yilmazkuday (2020) studies the effects of the COVID-19 cases in the U.S. on the S&P 500 Index using daily data. The study covers the period between 21 January 2020 and 6 August, 2020. This study utilizes a structural vector autoregression model (“VAR”) model. Yilmazkuday’s (2020) findings suggest that 1% rise in cumulative daily COVID-19 cases in the U.S. results in about 0.01% of a cumulative decrease in the S&P 500 Index on the following day (one day lag) and about 0.03% of a decrease after one month (30 days lag) indicating the COVID-19 negative impact on the U.S. stock market at one day and 30-days lag (Yilmazkuday, 2020).

Baker & al. (2020) quantified the impact of news related to COVID-19 on stock market volatility utilizing textual analysis and report that COVID-19 has had a more significant effect on stock market volatility than other similar diseases, such as Ebola (Baker et al., 2020). One of their interesting findings is that during the month of March 2020 (more specifically from 24 February, 2020 to 24 March 2020), there were 18 market jumps in 22 trading days. That surpasses any period in the past with comparative number of trading days. According to Baker & al. (2020), no other infectious diseases outbreak had a similar effect on the U.S. stock market volatility since the year 1985. Furthermore, Baker et al. (2020) argue that news related to pandemics and infectious diseases outbreaks since the year 1900 never had a similar impact on the daily market swings; including the 1918-1920 Spanish Flu pandemic and the influenzas pandemics of 1957-58 and 1968 (ibid.). They concluded that all the Covid-19 news, whether positive or negative, was the primary determinant of stock market movements from late February 2020 till early April 2020. Also, the frequency of sizeable daily stock market moves during this period is exceptional. They explicitly state that the COVID-19 period stands out for an extremely high frequency of sizeable daily stock market moves, stressing that it never happened in the past 120 years. The development of a pandemic caused such market fluctuations or even drove any significant daily stock market moves. However, their findings preclude that the lethality and adverse health effects of the novel
Covid-19 was the dominant driver of the stock market panic. They attest that the unprecedented governmental restrictions, travel restrictions, lockdown, mandatory business closures, other restrictions on business activity and social distancing can better explain the stock market reaction to the Covid-19 pandemic. Hence, the policy response to the COVID-19 pandemic provides a persuasive justification for its unprecedented effect on the stock market (Baker et al., 2020). Notwithstanding the evident and correct healthcare rationale for travel restrictions, social distancing mandates, and other containment policies, such policies lead to significant economic damage in both the short and long terms (Baker et al., 2020).

On the other hand, Valle-Cruz et al. (2020) conducted a comparative study on the difference between Financial Sentiment Analysis during the H1N1 pandemic and the COVID-19 pandemic. In their research, they utilize the Twitter platform to answer the question of whether the polarity driven by Twitter posts affects the behavior of stock market indices in pandemic seasons. They used sentiment analysis of the most-followed Twitter accounts in this realm and studied their relationship with the behavior of critical financial indices. They utilized four lexicons to determine polarity on Twitter. Their findings show that the period in which the markets reacted was 6 to 13 days after the information was shared and disseminated on Twitter in the COVID-19 season and 1 to 2 days for the H1N1 season. They also concluded that financial sentiment analysis is an essential technique to projecting the stock market, and polarity is the most widely used technique in the financial area. There is a relationship between the polarity in Twitter and the financial indices' behavior. Also, they stated that the most influential Twitter accounts during the pandemic season were The New York Times, Bloomberg, CNN News, and Investing, as those showed a significant relationship between sentiments on Twitter and the stock market behavior (Valle-Cruz et al., 2020). Although their research methodology is close to our thesis methodology, we disregard the comparison between COVID-19 and H1N1 as the two infectious diseases occurred at two different points in time. The dissemination of information and popularity of Twitter worldwide has multiplied since the H1N1 outbreak in 2009.

Another paper that investigates the COVID-19 news’ impact on stock market volatility is the “Covid-19 and stock market volatility” by Onali in 2020 (Onali, 2020). In his study, he uses GARCH (1,1) model and one-year data from April 2019 to April 2020 to investigate the effect of the changes in the announced numbers of Covid-19 cases and related deaths on the U.S. stock market represented by the Dow Jones and S&P500 indices. He studies changes in trading volume and volatility expectations, as well as day-of-the-week effects (Onali, 2020). One of his important findings is that the changes in the
number of cases and deaths related to Covid-19 drastically affected the volatility of the Dow Jones and S&P500, but there is little evidence that they have had a significant effect on the stock returns. One concludes that it is difficult to square the changes in the number of cases and deaths in the U.S. and six other countries with the U.S. stock market returns as it does not have a significant impact on the U.S. stock market returns. Nonetheless, he states that there is evidence of a significant positive impact, for some countries, on the conditional heteroscedasticity of the Dow Jones and S&P500 returns. Conditional heteroskedasticity is the non-constant volatility or, in other words, the general structural changes in volatility that are not related to prior period volatility. In addition, Onali claims that the Covid-19 crisis might have changed the standard relationship between volatility expectations and stock market returns (Onali, 2020).

Another study by Gormsen & al. (2020) from the University of Chicago tackles the COVID-19 effect on stock prices and growth expectations (Gormsen et al., 2020). They tend to study the impact of the COVID-19 outbreak and subsequent policy responses on short-term dividend futures. According to their paper, in order to study the expected impact of COVID-19 on the economy over the next few years, they studied the term structure of dividend prices. They leveraged data from the aggregate stock market and dividend futures to be able to quantify the evolvement of investors' expectations about economic growth over time in response to the coronavirus outbreak and subsequent policy responses from the beginning of the pandemic till June 2020. As of 8 June 2020, they forecasted that annual growth in dividends would go down 9% in the U.S. and 14% in the E.U. compared to 1 January 2020, and their forecast of GDP growth was down by 2.0% in the U.S. and 3.1% in the E.U. (Ibid). They argue that although the news about fiscal stimulus around 24 March 2020 pushed the stock markets and long-term growth upward a little, it did not increase short-term growth expectations significantly. Expected dividend growth has improved since 1 April 2020 in both the U.S. and the E.U. They concluded dividend futures could form a useful indicator during times of economic and financial distress, demonstrating how dividend futures in the U.S., E.U., and Japan could be a tool to derive a lower bound on projected growth in dividends and GDP, as well as an estimate of projected growth during the unprecedented COVID-19 crisis (Gormsen et al., 2020).

Another interesting paper studies the impact of the COVID-19 lockdown on stock market performance: evidence from Vietnam. The study explores the effects of the COVID-19 outbreak. Its following lockdown on daily stock returns an emerging market proxied by Vietnam; illustrating how Vietnam successfully recouped following the pandemic lockdown. The study uses panel data regression
models to analyze the effect of the daily number of COVID-19 confirmed cases during pre-lockdown and lockdown on daily stock returns of 723 listed firms in Vietnam from 30 January 2020 to 30 May 2020. The study validates the negative impact of the rising daily number of COVID-19 cases on stock returns in Vietnam. The study also concludes that the behavior and performance of the Vietnamese stock market was contradicting prior and post the nationwide lockdown. Although the COVID-19 pre-lockdown had a significant, adverse effect on Vietnam’s stock returns, the lockdown period had a significant, positive impact on the stock performance of the entire market and the different business sectors in Vietnam. The study concludes that Vietnam successfully controlled the pandemic, as indicated by the investors’ confidence and faith in the Vietnam government’s actions and decisions to combat COVID-19 (Gan et al., 2020).

2. Behavioral Finance And Investor Sentiment

Behavioral finance is a theoretical field of research which relates psychological theories to financial models in order to study and justify market anomalies. Behavioral finance studies investor behavior and how it affects the performance of stock markets from a psychological perspective. Since ethics and emotions influence financial performance and behavioral functions are used to analyze financial markets, behavioral finance has become an interesting research field. Despite the massive variety of concepts studied by behavioral finance, there is one that is gaining huge popularity and research attention in recent years: investor sentiment and its relationship with stock market activity (Yang, 2016).

Investor sentiment is a research area in the theoretical field of behavioral finance that analyses the emotional valence or the sentiment of investors and the way it influences stock market activity. Recently, the number of publications in this area has seen an increase, indicating its rising importance and relevance. There is no general agreement on the theoretical structure of behavioral finance nor on the investor sentiment research area till nowadays (Calzadilla et al., 2020). In their study, Calzadilla & al. (2020) used co-citation, bibliographic coupling and co-occurrence analysis to present an overview of the structure of investor sentiment. They concluded that investor sentiment is related to efficient market theory and behavioral finance theories. In addition, they concluded that investor sentiment is a relevant research field and that advances in computer science or theories based on physics or mathematics could further demonstrate the impact of investor sentiment on stock markets’ performance. (Calzadilla et al., 2020).
Investor sentiment is usually affected by news, events, rumors and social media. Social media sentiment is certainly a real-time indicator of investor sentiment and can be utilized as a risk factor in asset pricing frameworks as per Houlihan & al. (Houlihan et al., 2017). In their research, Houlihan and Creamer (2017) use textual based data and a specific market data derived call-put ratio, during the period from July 2009 to September 2012. They concluded that sentiment from social media and market data can be used as risk factors in an asset pricing framework (Houlihan et al., 2017).

Bollen & al. (2011) investigated how measurements of collective mood states, which were based on large-scale Twitter feeds, were correlated to the performance of the DJIA over time. They studied text content of daily Twitter feeds. Their results indicated that the accuracy of DJIA projections could be significantly enhanced by the inclusion of specific public mood dimensions but not others. Their accuracy level was 86.7% in predicting the daily up and down changes in the closing values of the DJIA using measures of public mood that was derived from Twitter. They demonstrated that daily variations in public mood states had a statistically significant correlation to daily changes in DJIA adjusted closing prices (Bollen et al., 2011).

3. Sentiment Analysis And Affective Computing

Medford & al. (2020) conducted an observational study to understand the early changes in Twitter activity, content, and sentiment in relation to the COVID-19 pandemic. They leveraged the high-volume Twitter data to analyze the public sentiment for the Covid-19 Outbreak. Their data set includes all tweets from all Twitter users who tweeted or retweeted or replied using the “COVID-19” hashtag between January 14th, 2020 to January 28th 2020 (Medford et al., 2020). They measured the frequency of keywords related to precautionary measures, vaccination, and racial prejudice. Later they conducted a sentiment analysis to quantify polarity and predominant emotions and subsequently conducted a topic modeling to identify and explore discussion topics over time. After evaluating 126,049 tweets from 53,196 unique users, they found out that the number of COVID-19-related tweets per hour rocketed upwards starting 21st of January 2020. Around half (49.5%) of all tweets expressed fear, and almost 30% expressed surprise. They were also able to conclude that the economic and political impact of the Covid-19 outbreak was the most discussed topic, while topics like public health risk and infection prevention were relatively the least discussed. Medford & al. (2020) concluded that tweets with negative sentiment closely echo the incidence of cases for the Covid-19 pandemic. They have also concluded that the frequency of tweets paralleled the number of infected individuals during the early stages of the Covid-19
pandemic. In addition, they also concluded that Twitter is a rich medium that can be utilized to analyze and study public sentiment in real-time and keep abreast of public health messages based on various users’ interests and emotions (Medford et al., 2020).

Sentiment Analysis is the process of computationally identifying and categorizing opinions from a piece of text and decide whether the writer’s attitude in relation to a particular topic or product is positive, negative or neutral. Nowadays, sentiment analysis is widely used to help understand how people feel in relation to a specific topic. The development of sentiment analysis overlaps the arising of social media on the web, which resulted in the copiousness of opinion data recorded in digital forms (Liu, 2015). Over the past two decades, sentiment analysis applications have outreached every potential realm, from consumer products, health care, tourism, hospitality, and financial services to social events and political elections. Sentiment analysis depends mainly on Natural Language Processing (“NLP”) and news, articles, or a social media platform like Twitter. Twitter is considered a treasure trove of sentiment. People worldwide express millions of reactions & opinions on almost every subject every millisecond of every day (Cambria, 2017).

As mentioned before, the term sentiment analysis generally refers to determining one’s attitude towards a particular target or topic. It refers specifically to the function of detecting the valence or polarity of a piece of text, whether it is positive, negative, or neutral (Mohammad, 2020). Sentiment analysis is considered one of the most popular applications of natural language processing and text analytics (Sarkar, 2019). All textual data can be categorized into two main categories of documents: factual and subjective. Factual documents portray some form of statements or facts with no specific feelings or emotions attached to them, also known as objective documents. However, subjective documents depict feelings, moods, emotions, and opinions. To that end, Sentiment analysis arguably works the most on subjective text, which includes people’s opinions, feelings, and their mood (Sarkar, 2019). Sentiment analysis is excessively utilized in the business world in tasks like analyzing corporate surveys, feedback surveys, social media data, and reviews for movies, places, commodities, and many more. The main notion behind is analyzing the reactions of people about a specific entity and taking insightful actions based on their sentiments.

Sentiment analysis is widely used to tackle the task of polarity detection. Most research studies use the terms “polarity detection” and “sentiment analysis” interchangeably due to the common definition of sentiment analysis as the NLP task that aims to categorize a piece of text as either positive or negative.
(Cambria, 2017). Although polarity detection is an important task of NLP, it is just one of the various problems and tasks that NLP solves in order to achieve human-like performance in sentiment analysis (Cambria, 2017). NLP is a theory-driven range of computational techniques for the automatic analysis and representation of human language. In his book, Sarkar (2019) states that NLP is simply the process of utilizing tools, techniques, and algorithms to process and analyze natural language-based data, that is normally unstructured (like text, speech, and so on) (Sarkar, 2019). Some would argue that sentiment analysis is a subarea of NLP. Theoretically speaking that is not accurate. In fact, sentiment analysis helped broadening the NLP research significantly by introducing many challenging and intriguing new research questions. The research literature over the past couple of decades indicated that rather than being a subproblem of NLP, sentiment analysis is more like an application or a special case of the full NLP (Liu, 2015).

In the finance industry, text analytics and NLP have the potential to automate multiple functions and tasks partially. NLP has been used in finance to amass real-time data on specific stocks, conduct algorithmic trading, predict stock movements, evaluate company regulatory filings, monitor company sentiment, anticipate client concerns, upgrade the quality of analyst reporting, understand and respond to news events and detect insider trading. Other possible applications in finance could be to help with risk modeling (topic modeling), check for regulatory compliance or to evaluate large volumes of research reports to detect more subtle changes. Possible applications in finance could be to check for regulatory compliance or to evaluate large volumes of research reports to detect more subtle changes in sentiment than can be discerned from analysts’ recommendations alone (Cambria et al., 2014).

Nowadays, the Social media hype has provided people with real-time content-sharing opportunities that allow them to create and share their own content, ideas, and opinions, with an unlimited audience of people worldwide in real-time with zero costs. Nonetheless, much of this data is basically unstructured as it is primarily aimed for human consumption and subsequently not easily nor directly machine-processable. However, the advancement in text mining and NLP through advanced machine learning techniques enable better utilization of such a huge amount of data.

Sasank & al. (2006) conducted a study called “Sentiment Analysis of Twitter Data for Predicting Stock Market Movements”. The study used two different textual representations, Word2vec and N-gram, for studying the public sentiments in tweets. They employed sentiment analysis and supervised machine learning principles to the tweets derived from twitter and analyzed the correlation between
stock market movements of a company and sentiments in tweets. They classified the tweets into three categories: positive, negative and neutral. They concluded that there is a strong correlation between the movements of the share price of a company to the public opinions or emotions about that company as disseminated on Twitter through tweets (Sasank et al., 2016). Speaking of textual representations, it is worth noting that the choice of the training algorithm and the hyper-parameter selection is a task-specific decision (Milkov et al., 2013). Milkov et al. argue in their research that the most crucial decisions that affect the performance of textual mining are the choice of the model, the size of the vectors, the subsampling rate, and the size of the training window. They also argue that word vectors can be rather meaningfully combined using just simple vector addition. They also suggest representing the phrases with a single token for learning representations. Both of those two approaches combined provide a powerful yet simple technique to represent longer pieces of text while having minimal computational complexity (Milkov et al., 2013).

Another study on this topic that we find compelling is “Making Trading Great Again: Trump-based Stock Predictions via doc2vec Embeddings” by Rifath Rashid from Stanford University. Rashid (2019) put forth the question of how tweets made by an influential policymaker like President Donald Trump can model and predict the stock market correctly using sentiment analysis. That is very close to our thesis question, which tackles how tweets can model stock market performance. Rashid stated that the paramount importance of Twitter as a sentiment detector and stock market determinant became obvious during April 2013; when the Associated Press’s account got hacked and false information led to an immediate 143.5 points drop in the Dow Jones Industrial Average (“DJA”) and $136 billion loss by the Standard & Poor (“S&P 500”); for no fundamental or technical reason other than panic and fear in the market following the false tweet (Rashid, 2019). The paper also studied how developments and advancements in distributed word representations can better analyze contextually rich sentences better than conventional sentiment analysis. Rashid (2019) was trying to prove whether contextually rich word representations of Trump tweets could significantly forecast stock market changes utilizing deep machine learning based on document embeddings of tweets and feeding those embeddings into a neural network to forecast stock price movements. (ibid.). The paper used the python programming language and API to attain Trump tweets for the year 2019 and used a publicly available dataset for all remaining tweets of Donald Trump from the year 2010 to the year 2018; due to the restrictions, Twitter places on how far developers can go back in search. The average number of tweets per day is 13.4, and the max number of tweets in one day is 160 tweets (Rashid, 2019).
The research depended on the Python “gensim library” to develop the doc2vec model. The data cleansing: like removing stop-words, for instance, was done by using the “NTLK library” and converting all words to lower case (ibid.). Our thesis also utilized the “NTLK Library” for data cleansing and preprocessing.

Sentiment Analysis is the process of computationally analyzing, detecting and quantifying opinions from piece of text and decide whether the writer’s notion or attitude in relation to a particular topic or product is positive, negative or neutral. Nowadays sentiment analysis is widely used to help understand how people feel in relation to a specific topic. The development of sentiment analysis overlaps the arising of social media on the web, which resulted in the copiousness of opinion data recorded in digital forms (Liu, 2015). Over the past two decades, sentiment analysis applications have outreached every potential realm, from consumer products, health care, tourism, hospitality, and financial services to social events and political elections. Sentiment analysis depends mainly on Natural Language Processing (“NLP”) and news, articles or a social media platform like Twitter. Twitter is considered treasure trove of sentiment. People around the globe express millions of reactions & opinions on almost every subject every millisecond of every day (Cambria, 2017).

As mentioned before, the term sentiment analysis generally refers to determining one’s attitude towards a particular target or topic. It refers specifically to the function of automatically determining the valence or polarity of a piece of text, whether it is positive, negative, or neutral (Mohammad, 2020). Sentiment analysis is considered among the most common applications of natural language processing and text analytics (Sarkar, 2019). All textual data may be categorized into two either factual or subjective documents. Factual documents usually include informative statements or facts with no sentiment, feelings or emotion attached to them, which is also known as objective documents. However, subjective documents depict feelings, mood, emotions, and opinions. The challenging type of textual data are the subjective documents. Sentiment analysis arguably works the most on subjective text, which includes people’s opinions, feelings, and their mood (Sarkar, 2019). Sentiment analysis is excessively utilized in analyzing corporate surveys, feedback surveys, social media data, and reviews for movies, places, commodities, and many more. The main notion behind is analyzing the reactions of people about a specific entity and taking appropriate well-thought actions according to the sentiments.

Polarity detection is the most common and popular task of sentiment analysis. Most research studies use the terms “polarity detection” and “sentiment analysis” interchangeably, due to the common
definition of sentiment analysis as the NLP task that aims to categorize a piece of text as either positive or negative (Cambria, 2017). Although polarity detection is an important task of NLP, it is just one of the various problems and tasks that NLP solves in order to achieve human-like performance in sentiment analysis (Cambria, 2017). NLP is a theory-driven range of computational techniques for the automatic analysis and representation of human language. In his book, Sarkar states that NLP is simply the process of utilizing tools, techniques, and algorithms to process and analyze natural language-based data, that is normally unstructured. (Sarkar, 2019).

In the finance industry, text analytics and NLP have the potential to partially automate multiple functions and tasks. NLP has been used in finance to amass real-time data on specific stocks, conduct algorithmic trading, predict stock movements, evaluate company regulatory filings, monitor company sentiment, anticipate client concerns, upgrade quality of analyst reporting, understand and respond to news events and detect insider trading. Other possible applications in finance could be to help with risk modeling (topic modeling), check for regulatory compliance or to evaluate large volumes of research reports to detect more subtle changes. Possible applications in finance could be to check for regulatory compliance or to evaluate large volumes of research reports to detect more subtle changes in sentiment than can be discerned from analysts’ recommendations alone (Cambria et al., 2014).

Nowadays, the Social media hype has provided people with real-time content-sharing opportunities that allow them to create and share their own contents, ideas, and opinions, with an unlimited audience of people worldwide real-time with zero costs. Nonetheless, much of this data is basically unstructured as it primarily aimed for human consumption and subsequently not easily nor directly machine-processable. However, the advancement in text mining and NLP through advanced machine learning techniques enable better utilization of such huge amount of data.

In 2006, Sasank & al. conducted a study called “Sentiment Analysis of Twitter Data for Predicting Stock Market Movements”. The study used two different textual representations, Word2vec and N-gram, for studying the public sentiments in tweets. They employed sentiment analysis and supervised machine learning principles to the tweets derived from twitter and analyzed the correlation between stock market movements of a company and sentiments in tweets. They classified the tweets into three categories: positive, negative and neutral. They concluded that there is a strong correlation between the movements of the share price of a company to the public opinions or emotions about that company as disseminated on twitter through tweets (Sasank et al., 2016). Speaking of textual representations, it is
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instance was done by using the “NTLK library” and converting all words to lower case (ibid.). Our
thesis also utilized the “NTLK Library” for data cleansing and preprocessing.
Rashid (2019) concluded their study with a demonstration of the principle that trading based on the sentiment of tweets made by an influencing public figure/politician like President Donald Trump is well-grounded. They proved that by being able to achieve consistent non-negative returns using only a basic trading strategy for different public companies (Rashid, 2019). They also stated that although they relied on document embeddings for their empirical success in the financial domain, it is recommended that future work considers trying a weighted average of word embeddings. They also recommended that future projects with access to microscale stock information should look deeper into the lag times in minutes and seconds on stock price movements. Although in this study they were limited to macroscopic end-of-day prices, Rashid & al. mentioned that minor explorations with lag times in days showed little change (Rashid, 2019). That was demonstrated in our findings in this thesis; explorations with lag times in days changed the results. In the case of Covid-19, lag times in days had a larger impact on the results compared to the Trump tweets case.

4. Other Macroeconomic Determinants Of Stock Market

Since the beginning of the 20th century, economists, investors, and policymakers aim to forecast the tendency of share prices, which inarguably rely on foreign and domestic macroeconomic factors (Demir, 2018). In one interesting paper by Chen (2008), he studied the behavior of the SP500 index and pursued to study the main determinants of stock market recessions over the 1957–2007 period. His findings from the monthly data showed that the yield curve spreads, and the inflation rate could significantly predict the recessions (Demir, 2018; Chen, 2008).

In his paper, Chen (2008) investigated the ability of macroeconomic factors in forecasting recessions in the stock market or as commonly known bear markets. Chen evaluated macroeconomic variables like interest rate spreads, inflation rates, aggregate output, unemployment rates, federal funds rates, federal government debt, and nominal exchange rates. Chen (2008) concluded that yield curve spreads and inflation rates are the main predictors of recessions in the US stock market proxied by monthly data of S&P 500 price index. Furthermore, his study suggested that it is simpler to predict bear markets using macroeconomic variables (Chen, 2008).

A study was conducted on the relationship between stock exchange and interest rate; given that they are two crucial determinants of economic growth of a country (Alam et al., 2009). The study tackles evidence supporting the existence of share market efficiency based on the monthly data from January
1988 to March 2003. The study demonstrates empirical relationship between stock index and interest rate for fifteen developed and developing countries. One of the important findings by this study is that stationarity of market return is tested and found none of this stock market follows random walk model, means not efficient in weak form. Further investigation was conducted where relationship between share price and interest rate, and changes of share price and changes of interest rate were determined through both time series and panel regressions. It is concluded that interest rate has significant negative relationship with share price and for six countries it is found that changes of interest rate has significant negative relationship with changes of share price. The study suggests that if the interest rate is controlled for these countries, it will substantially help these countries’ stock exchange through the forces of supply and demand (Alam et al., 2009).

5. **Capital Markets Global Integaration**

Globalization ignited the research interest about the integration of stock markets throughout the world, and the financial crisis of 2008 brought an increased attention to the topic when capital markets around the globe fell like dominos. Potharla & al. (2012) applied correlation t-test on the month-wise average prices of BSE-Sensex, NYSE, NASDAQ, S&P500, Hang Seng, Nikkei225, SSE Composite index and FTSE100 to study the integration between markets. Their results show that there is a considerable integration between international financial markets. FTSE100 (The European index) demonstrated strong correlation with all the US stock market indices and with Nekkei225, the Japanese stock market index (Potharla & al., 2012). Copeland & al. (1998) used the Dow Jones and industry indices to conclude the USA markets have statistically significant one-day lead over markets in Europe and Asia. They also concluded that no significant leads extend further than one day. They have also stated that Lead/lag relationships might result in yield enhancement, possibly even arbitrage, through trading futures in some markets (Copeland et al., 1998).

Given the fact that capital markets globally operate in different time zones and subsequently have different working hours, many authors studied the correlations between stock markets in the world, using same-day or lagged correlations between financial market indices. Leonidas (2012) conducted a study to analyze whether researchers should use all indices on the same day or lagged indices (Leonidas, 2012). The study utilized 79 stock market indices from around the world and studied their correlation
structure, the eigen values and eigen vectors of their correlations under different time periods and volatility, as well as the differences between the working hours of the stock exchanges in order to analyze the possible time zone effects. The study concluded that stock market indices which have conciding hours with the NYSE have larger correlations with the S&P500 when not lagged, and that indices that have non-conciding hours with NYSE show larger correlations when their indices are compared with the lagged S&P500 (i.e. the S&P500 of the previous day) (Leonidas, 2012).

Furthermore, Eum & al. (1989) stated that changes in the US market reflect on the movements of the other global markets on the following day; and that the exact markets on the same day show low correlations (Eum et al., 1989). Becker & al. (1992) demonstrated that the correlation between the Japanese and US stock markets is highly significant when using the lagged US market returns; meaning that the US markets movements is reflected on the next day performance in Japan (Becker et al., 1992).
3. Thesis Objective

The existing literature has established the relationship between news and social media platforms on investors' sentiment and, subsequently stock market. However, the literature reveals that not many studies have been carried out regarding measuring volatility during pandemics, especially the COVID-19 pandemic. Furthermore, although studies are tackling the effect of COVID-19 news on investors' sentiment and the stock market, there are no adequate studies utilizing the Twitter platform and Tweets as a driver of investors’ sentiment. In addition, no studies are analyzing the COVID-19 investors’ sentiment impact on stock markets globally and how the dissemination of COVID-19 information and opinions through the Twitter platform affected volatility and returns across the developed markets worldwide. Also, most of the current COVID-19 studies have a limited time frame; where the research is covering one or two months only; which is not very representative of the fluid circumstances that the whole world witnessed in 2020 and that impacted stock markets globally. Therefore, this paper will attempt to fill the gap in the literature and make an attempt to address the question of how accurately COVID-19 Twitter posts were able to model the movement and volatility of stock markets globally from the 4th of January 2020 till the 21st of December 2020.

As mentioned earlier, our aim in this thesis was to address the question of how accurately COVID-19 Twitter posts were able to model the movement and volatility of stock markets globally. We utilized sentiment analysis and the Twitter platform to identify the emotional valence of the COVID-19 tweets and subsequently model how tweeting about COVID-19 affects the global stock market indices in terms of trading volume, volatility and returns. We demonstrated how global stock markets are integrated and how contagious are stock market movements around the globe. We utilized text-mining and sentiment analysis to detect the polarity of COVID-19 related tweets and regress them using a classical GARCH (1,1) model against the log-returns of six global developed market indices in order to demonstrate how the investor sentiment during the COVID-19 pandemic influenced stock markets globally.

For each model, our H0 or null hypothesis was that the investor sentiment based on the COVID-19 tweets polarity has no impact on the stock index volatility. Our H1 or Alternative Hypothesis was that the investor sentiment has an impact on the stock market volatility represented by each index.

H0: The COVID-19 tweets polarity had no impact on the stock index volatility.

H1: The COVID-19 tweets polarity impacted the stock index volatility.
4. Thesis Data And Methodology

This chapter discusses our data, data sources, and thesis methodology. In performing our analysis, we conducted data cleansing, preprocessing, and sentiment analysis. We also analyze the descriptive statistics of the dependent and the independent variables used in the analysis. Furthermore, we discuss in this chapter our selected econometric model.

As mentioned earlier in the literature chapter, Houlihan and creamer (2017) used textual based data and a specific market data derived call-put ratio, during the period from July 2009 to September 2012. They concluded that sentiment from social media and market data can be used as risk factors in an asset pricing framework (Houlihan et al., 2017). So, news and opinions shared on social media can influence investors sentiment and consequently drive stock market fluctuations and performance in terms of volatility and returns.

In our thesis, we study how the investor sentiment in relation to the COVID-19 pandemic influenced stock markets globally and how stock markets globally are integrated and contagious. To determine investor sentiment, we used text mining and NLP to conduct sentiment analysis on COVID-19 related tweets and get the daily polarity of those tweets. That is in consistence with ((Valle-Cruz et al., 2020); (Medford et al., 2020); (Rashid, 2019); (Bollen et al., 2011); (Sasank et al., 2006)). Also, in consistence with the literature, we used Twitter as it is considered treasury of sentiment especially during the COVID-19 pandemic time. Unarguably there were an abundance of misinformation and biased opinions when it comes to COVID-19 on social media. As such, we decided to study the tweets made by credible market-driving sources only we filtered that to the official twitter accounts of WHO, CNN, BBC, NYTimes, DW news and Reuters. As those twitter accounts had the highest impact during the COVID-19 pandemic and that was also demonstrated by the previous literature (Valle-Cruz et al., 2020).
# 1. Data Sources

<table>
<thead>
<tr>
<th>Variable</th>
<th>Method of collection</th>
<th>Source</th>
<th>Duration</th>
</tr>
</thead>
</table>
| **Stock market returns**        | Using the python programming language; we imported from *Yahoo! Finance* the adjusted closing prices for 6 developed market indices, namely S&P500, Dow Jones Industrial Average (DJIA), Nasdaq, CAC40, DAXI, Nikkei225. We then calculated the returns and log returns for each index. | Yahoo! Finance Market Indices:  
  - S&P500  
  - Dow Jones Industrial Average (DJIA)  
  - Nasdaq  
  - CAC40  
  - DAXI  
  - Nikkei225 | The index adjusted closing prices were imported for the duration from January 4th, 2020 till December 21st, 2020 (337 days). |
| **Investor sentiment based on the daily polarity of Covid-19 related tweets** | We collected tweets related to Covid-19 specific search words. Our sample of tweets was extracted from specific credible user accounts in the English language. Our tweets were extracted using the python programming language, Twitter’s API, its advanced search tool ([https://twitter.com/search-advanced](https://twitter.com/search-advanced)) and a specific code that we developed (Appendix 1). | Python Programming language  
Twitter  
Twitter API  
Tweepy library  
The following Twitter accounts:  
  - WHO  
  - Reuters  
  - CNN  
  - NYTimes  
  - DW news  
  - BBC Breaking | The tweets were collected for almost one year from January 4th, 2020 till December 21st, 2020 (337 days). The average number of tweets collected is 15 tweets per day and the median is 10 tweets per day. |
| **Interest rate- US treasury bills with 3 months maturity** | We downloaded the 3-month Treasury Bill Rate from the official website of the U.S. Department of The Treasury. | U.S. Department of The Treasury | The 3-month treasury bill rates were imported for the duration from January 4th, 2020 till December 21st, 2020 (337 days). |
| **Inflation rate**              | We downloaded 10-year treasury inflation-indexed security with constant maturity     | U.S. Bureau of Labor Statistics                                        | The same duration from January 4th, 2020 till December 21st, 2020        |
a) Covid-19 Related Tweets

From January 4th to December 21st, 2020, we collected tweets in the English language using the Python programming language, Twitter’s API, and its advanced search tool (https://twitter.com/search-advanced). We excluded Retweets, Replies, and mentions. In that way, we collected tweets made by the official Twitter account of our prespecified sources only, excluding any noise or misinformation. Moreover, The Twitter stream was filtered by Twitter’s advanced search algorithm and the Tweepy Library resulting in a representative subset of tweets. We specified vital search words for the tweets we want to collect in our code. Our search words included: Corona, Coronavirus, Covid19, Covid, COVID-19, and pandemic. Our collected metadata from tweets included four variables: tweet text, timestamp, user, and search word. We cleaned our dataset to ensure that all our tweets are unique tweets and duplicates.

Our choice of the Twitter platform is consistent with the literature. Twitter is widely used all over the world to track trends and disseminate information including health information. On January 21, 2020, the CDC activated its Emergency Operations Center, and the WHO released its first situation report about COVID-19, initiating significant media attention (Medford et al., 2020). As per Medford & al. (2020) observational study on leveraging High-Volume Twitter Data to Understand Public Sentiment for the COVID-19 Outbreak, Twitter is a rich platform and valuable communication medium that can be substantially utilized to study the public sentiment in real-time and target the public health messages based on user interest and emotion (ibid.). Amid the COVID-19 pandemic, social media has become raged with information and opinions about the virus. It is inarguable that Twitter specifically played a vital role in the sharing and dissemination of information and opinions in real-time around the globe. The Twitter effect during the COVID-19 pandemic was felt across all fields, whether the financial, business, academic, and medical fields (Rosenberg, 2020).

b) Stock Market Returns

Using our Python Jupyter Notebook, we imported the adjusted closing prices of 6 indices that are representative of developed markets in USA, Europe and Asia from Yahoo! Finance, using the below mentioned code. We imported the macroscopic daily prices of 6 indices. Our indices include S&P 500
(GSPC), Dow Jones Industrial Average (DJIA), Nasdaq (IXIC), CAC 40 Index (FCHI) and Nikkei 225 (N225).

**Getting Indices Returns: Global Stock Market Returns**

In [153]:
```
start = dt.datetime(2020,1,4)
end = dt.datetime(2020,12,21)
symbols = ["GSPC", "DJIA", "IXIC", "GDAXI", "FCHI", "N225"]
stocksUSA = web.get_data_yahoo(symbols, interval='d', start=start, end=end)
stocksUSA.head()
```

Out[153]:
```
          Symbols    Adj Close    Close    Open    Date
2020-01-04 GSPC   3124.150000   3124.400000   3123.250000  2020-01-04
2020-01-06 GSPC   3126.450000   3126.100000   3125.000000  2020-01-06
2020-01-07 GSPC   3125.600000   3125.350000   3124.200000  2020-01-07
2020-01-08 GSPC   3125.500000   3125.450000   3124.290000  2020-01-08
2020-01-09 GSPC   3124.900000   3124.650000   3123.390000  2020-01-09
```

5 rows x 25 columns

In [154]:
```
pricesUSA = stocksUSA["Adj Close"]
pricesUSA.head()
```

Out[154]:
```
          Symbols    Adj Close    Close    Open    Date
2020-01-04 GSPC   3124.150000   3124.400000   3123.250000  2020-01-04
2020-01-06 GSPC   3126.450000   3126.100000   3125.000000  2020-01-06
2020-01-07 GSPC   3125.600000   3125.350000   3124.200000  2020-01-07
2020-01-08 GSPC   3125.500000   3125.450000   3124.290000  2020-01-08
2020-01-09 GSPC   3124.900000   3124.650000   3123.390000  2020-01-09
```

- **S&P 500 (GSPC):** The S&P 500 is considered the ultimate measure of large-cap U.S. equities and operates as the foundation for a wide range of investment products. The index includes 500 leading companies and captures approximately 80% coverage of available market capitalization. The S&P 500 index is a capitalization-weighted index and the 10 largest companies in the index account for 26% of the market capitalization of the index. The 10 largest companies in the index, in order of weighting, are Apple Inc., Microsoft, Amazon.com, Facebook, Alphabet Inc. (class A & C), Berkshire Hathaway, Johnson & Johnson, JPMorgan Chase & Co. and Visa Inc. S&P 500 is based in the United States of America and is presented in the following exchanges are NYSE, NASDAQ, Cboe BZX Exchange.

- **Dow Jones Industrial Average (DJIA):** The Dow Jones Industrial Average (DJIA) is a stock market index that measures the stock performance of 30 large companies listed on stock exchanges in the United States. It is weighted using a weighted arithmetic mean. It includes stocks listed on the NYSE and NASDAQ.
NASDAQ (IXIC): The NASDAQ Composite is a stock market index that includes almost all stocks listed on the Nasdaq stock market. Along with the Dow Jones Industrial Average and S&P 500 Index, it is one of the three most-followed stock market indices in the United States. The composition of the NASDAQ Composite is heavily weighted towards companies in the information technology sector. The NASDAQ-100, which includes 100 of the largest non-financial companies in the Nasdaq Composite, accounts for over 90% of the NASDAQ Composite's movement.

CAC 40 (FCHI): CAC 40 is a benchmark French stock market index. The index represents the 40 most significant stocks among the 100 largest market caps on the Euronext Paris. The index is calculated based on market capitalization-weighted average calculations.

The DAX Performance Index (GDAXI): The DAX is the German stock index; it is a blue-chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange.

Nikkei 225 (N225): Nikkei 225 is a stock market index for the Tokyo Stock Exchange (TSE). It is a price-weighted index, operating in the Japanese Yen (JP¥), and its components are reviewed once a year. The Nikkei measures the performance of 225 large, publicly owned companies in Japan from a wide array of industry sectors.
2. Descriptive Statistics

This table shows descriptive statistics (mean, variance, standard deviation, coefficient of variation, skewness and kurtosis) of our independent variables; over the time period from the 13th January 2020 till 21st December 2020. By looking at Table 1 below, all the three variables have mean and median that are close; indicating that they are symmetrical and normally distributed. we will find that polarity has the highest and only positive mean while the interest rate has the lowest mean. Consequently, Polarity has the highest skewness, and the interest rate has the lowest skewness. Neither of the three variables is correlated.

Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Polarity</th>
<th>IR_90_days</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>0.0401</td>
<td>-0.0180</td>
<td>-0.0116</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>0.0340</td>
<td>0.1941</td>
<td>0.1547</td>
</tr>
<tr>
<td><strong>Variance</strong></td>
<td>0.0089</td>
<td>0.018709</td>
<td>0.007162</td>
</tr>
<tr>
<td><strong>Standard Deviation</strong></td>
<td>0.0944</td>
<td>0.4406</td>
<td>0.3933</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td>0.6334</td>
<td>-4.7276</td>
<td>0.4170</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>7.3062</td>
<td>84.0343</td>
<td>17.6454</td>
</tr>
</tbody>
</table>

Correlation Matrix Table

<table>
<thead>
<tr>
<th></th>
<th>Polarity</th>
<th>Interest Rate</th>
<th>Inflation rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polarity</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest Rate</td>
<td>0.033612</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Inflation Rate</td>
<td>0.018709</td>
<td>0.007162</td>
<td>1</td>
</tr>
</tbody>
</table>
3. Methodology

Figure 3: The Overall Methodology Of Our Thesis

Figure 3 is a high-level illustration for our methodology. We utilized the python programming language and the Twitter developers’ API to retrieve COVID-19-related tweets. Our algorithm excluded replies and retweets, capturing only original contributes. We leveraged Twitter API and tweepy library to import tweets from the before-mentioned Twitter accounts starting from the 4th of January 2020 till the 21st of December 2020. Our code excluded replies, and retweets. We imported only COVID-19-related tweets ensuring that the tweets captured include specific search words. Our search words were “COVID-19, Covid-19, Corona, Coronavirus, COVID-19, pandemic.”

<table>
<thead>
<tr>
<th>Twitter Account</th>
<th>Count of Tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>World Health Organization (WHO)</td>
<td>2,232</td>
</tr>
<tr>
<td>Reuters</td>
<td>1,531</td>
</tr>
<tr>
<td>CNN</td>
<td>933</td>
</tr>
<tr>
<td>NYTimes</td>
<td>312</td>
</tr>
<tr>
<td>DW news</td>
<td>292</td>
</tr>
<tr>
<td>BBC Breaking</td>
<td>180</td>
</tr>
</tbody>
</table>
We consolidated all the extracted tweets by date and time in a dataset; such that we had a dataset of dates, tweets and the source. We then conducted pre-processing on this data set. As illustrated below in Figure 4, our pre-processing included tokenization, data cleansing: Removing special characters and capital letters, removing stop words, stemming, lemmatization, normalization and a syntactics Layer. The syntactics layer preprocesses text ways that transform informal text to basic plain English, normalize inflected forms of verbs and nouns, and simplify basic sentence structure (Cambria, 2017). To further clarify; syntax refers to the order or arrangement of words in one phrase in a way that make those words understandable and grammatically sound. In NLP, syntactic analysis is utilized to assess how the natural language aligns with the grammatical rules. Computer algorithms are utilized to apply grammatical rules to a group of words so that other preprocessing layers do not distort the meaning.

*Figure 4: The Preprocessing of The Tweets*

![Diagram](image)

Our API extracted 5000 tweets over the period from 4th of January 2020 till 21st of December 27, 2020. We used the NTLK library to preprocess tweets. After data pre-processing and cleansing, we calculated the weighted sentiment for each tweet and then the weighted sentiment for each day; as shown below in Figure 5. Thus, we had a new data set of days and the polarity of each day indicating the investor sentiment on that day.
We then used the adjusted closing price for six indices that represent the developed and most liquid markets around the globe (United states, Europe and Asia). Our indices included S&P 500 (“GSPC”) that represents the largest company stocks in different sectors and industries in the USA, as well as Dow Jones Industrial Average (“DJIA”) (“DJI”), Nasdaq (“IXIC”), CAC (“FCHI”), DAXI (“GDAXI”) and Nikkei 225 (“N225”).

Given that a time series data with a unit root then it is not stationary, thus we cannot apply Autoregressive (“AR”), Autoregressive conditional heteroskedasticity (“ARCH”) or General Autoregressive heteroskedasticity (“GARCH”) models (McAleer et al.,2002). If the data series is non-stationary, it means the mean is changing over time. Stock market prices is a form of time series data that is non-stationary; meaning that it does not have a constant a constant value over time and the mean is changing over time. Thus, when data fit a statistical distribution in one time period, the non-stationarity may cause the parameter of the distribution to change in subsequent periods. And given that the adjusted closing prices is non-stationary and will distort our GARCH (1,1) model; we need to make our data series (Stock market adjusted closing prices) stationary by taking one difference or in other words differencing to remove trends. That de-trending was achieved by calculating the returns and log returns of each index. Thus, we were able to overcome this non-stationarity problem and get stationary data that has a constant value over time and can be used in time series models like GARCH (1,1). Figure
6 below shows the difference between stationary indices returns and non-stationary indices closing prices when both are plotted.

*Figure 6: Stationary Returns vs. Non-Stationary Prices*
Then we used the 3-months treasury yield rates for the period under study (from 1st of January 2020 till 21st of December 2020). The 3-months treasury bill rate is the yield received for investing in a government issued treasury security which matures in 3 months. The 3-months treasury yield is included on the shorter end of the yield curve and is vital when looking at the overall US economy. In addition, we downloaded the daily 10-Year Treasury Inflation-Indexed Security, with Constant Maturity. The 3-months treasury bill rate is the yield received for investing in a government issued treasury security which matures in 3 months. The 3-months treasury yield is included on the shorter end of the yield curve and is vital when looking at the overall US economy. In addition, we downloaded the daily 10-Year Treasury Inflation-Indexed Security, with Constant Maturity. The Consumer Price Index (CPI) is an indicator of the mean change over time in the prices paid by urban consumers for a market basket of consumer goods and services (FRED). Furthermore, we calculated the daily change in both in order to overcome the issue of stationarity and seasonality as well.

Subsequently, our data set consisted of the daily macroscopic indices returns, daily polarity based on the covid-19 tweets, daily change in treasury bill rates, and daily change in inflation rates in U.S.A. Our dependent variable is each index daily returns and our independent variables are the polarity, daily change in interest rates and daily change in inflation rates.

\[
Y \{1-5\}: \text{ Daily log returns of the 6 global indices \{GSPC, DJI, IXIC, FCHI, DAXI & N225\}}
\]

\[
X1: \text{ COVID-19 polarity/ investor sentiment.}
\]

\[
X2: \text{ change in the U.S. treasury bill rates.}
\]

\[
X3: \text{ change in U.S. inflation rates.}
\]
4. Sentiment Analysis

We conducted all the data processing and analysis utilizing the Python software, version 3.6.1 (Python Software Foundation). Generally, our data preprocessing included: Tokenization, Data cleansing: Removing punctuations, special characters and capital letters, removing stop words, and a Syntactics Layer: The purpose of the syntactics layer is to preprocess text in a way that informal text is reduced to plain English, inflected forms of verbs and nouns are normalized, and basic sentence structure is made clearer and more explicit (Cambria, 2017). After that, we conducted Stemming. Once we had a vector representation of a bag of words, we conducted polarity detection or identifying emotional valence where we applied unsupervised Machine Learning algorithms for determining the degree of polarity for each word based on the NLTK library. Finally, we calculated the weighted average sentiment for each day.

Prior to commencing the process of sentiment analysis and modeling; it is crucial that a series of specific steps are conducted (Hafsa, 2018). Those steps include cleaning, preprocessing, and normalizing text. That is considered one of the essential stages for any NLP pipeline. Preprocessing helps with standardization across a document corpus, which leads to meaningful features and reduces noise that can be introduced due to many factors, such as irrelevant symbols, special characters, XML and HTML tags, and so on. In our Jupyter Notebook (Python code), we built text_normalizer that can achieve our text normalization needs utilizing the Beautifulsoup library the NLTK package. The NLTK package is the Natural Language Toolkit package provided by Python for Natural Language Processing tasks (Hafsa, 2018). The main pillars of our text normalization pipeline are as follows:

- **Tokenization**: Tokenization means the ripping or splitting a whole paragraph into individual sentences or words.

- **Cleaning text**: Cleaning data means removing unnecessary content like HTML tags, as they do not make a difference when analyzing sentiment. Thus, we need to make sure we exclude them before mining features to ensure clean data with no unnecessary noise.

- **Expanding contractions**: In the English language, contractions are reduced versions of words. These reduced versions of existing words or phrases are created by removing specific letters and sounds. Often, vowels are removed from the words. Examples include “do not” to “don’t” and “I would” to
“I’d”. Contractions pose a problem in text normalization because we must deal with special characters like the apostrophe and we also must convert each contraction to its expanded, original form (Hafsa, 2018).

- **Removing special characters:** Furthermore, removing special characters and symbols that add to the noise in unstructured text is one more vital task for data cleansing, preprocessing and normalization. It has been established that simple regexes can be used to achieve this. In our python code, Our remove_special_characters(...) function removed special characters (Hafsa, 2018).

- **Stemming and lemmatization:** Stemming and Lemmatization are Text Normalization (or sometimes called Word Normalization) techniques in the field of Natural Language Processing that are used to prepare text, words, and documents for further processing. In other words, lemmatization is changing different forms of a word to its root form as found in the dictionary (e.g., “viruses” to “virus” or “went” to “go”) (Sarkar, 2019). Word stems are basically the root form or base of commonly used words; whereby adding affixes, like prefixes and suffixes, to the stem results in new words (Hafsa, 2018). A simple example is PLAYS, PLAYING, and PLAYED, which have the word root stem PLAY. The NLTK package offers an array of stemmers, like the PorterStemmer and LancasterStemmer (Sarkar, 2019). Lemmatization is very similar to stemming, where we remove word affixes to get to the base form of a word.

- **Removing stop words:** Stop words mean all words that have little or no significance. Words like “a,” “an,” “the,” and so on are stop words. In our code, we used the standard English language stop words list from NLTK. The remove_stopwords(...) function removed stop words.

  Using a word cloud, we visualized the top reoccurring words with larger font size representing greater frequency. The following diagram shows a word cloud for the raw tweets before processing and another word cloud for the tweets after pre-processing. Word cloud for our raw tweets before data cleansing, as shown in Figure 7 and a second word cloud after we pre-processed our tweets, as shown in Figure 8.
Figure 7: Word Cloud For COVID-19 Tweets Before Preprocessing

Figure 8: Word Cloud for COVID-19 Tweets After Tweets Preprocessing

Sentiment analysis can be conducted using unsupervised machine learning or supervised machine learning and deep learning. Unsupervised machine learning can be employed using semantic
orientation approach which depends on the usage of previously done lexicons of sentiment words
(Lexicon is a Bag of words or online dictionary) or ready to use packages like the NLTK packages.
For lexicon-based approaches, a sentiment is characterized by its semantic orientation and the
intensity of each word in the sentence. This depends on a pre-defined dictionary classifying negative
and positive words. For example, one tweet or one text message would be represented by bag of
words. After allocating individual scores to each of those words, final sentiment is calculated by
some taking an average or weighted average of all the sentiments.

In our thesis, we used unsupervised lexicon-based machine learning. We specifically used the
NTLK package or more specifically TextBlob to conduct sentiment analysis. TextBlob is a python
library for NLP, that is built upon the NLTK package. It provides an easy-to-use interface to the
NLTK library and can be employed to conduct different NLP tasks ranging from parts-of-speech
tagging, sentiment analysis, language translation, text classification, and noun phrase extraction. That
is, TextBlob actively uses NLTK to run its tasks. NLTK is a library which gives an easy access to a
lot of lexical resources and preforms tasks like categorization, classification and many other tasks.
The lexicon utilized in the TextBlob library is “en-sentiment.xml”. It is a sentiment lexicon (in the
form of an XML file) which provides both polarity and subjectivity scores. The scores from TextBlob
are normalized scale as compare to AFINN lexicon. TextBlob returns polarity and subjectivity of a
sentence. TextBlob depends on a weighted average sentiment score. Polarity lies between -1 and 1,
where -1 defines a negative sentiment and 1 defines a positive sentiment. Furthermore, negation
and/or negative words inverse the polarity. Subjectivity extends between [0,1]. Subjectivity quantifies
the amount of opinion and information contained in the text. The higher subjectivity means that the
text contains opinion rather than factual phrases or information. TextBlob has an additional
parameter: intensity. TextBlob further quantifies subjectivity by looking at the ‘intensity’. Intensity
determines if a word modifies/ intensifies the next word; for example (‘very sad’ or ‘very delighted’).

As shown in Figure 9 below, we used the TextBlob library to calculate the polarity of each tweet
and then we grouped by date to calculate the weighted average polarity by day.
As mentioned before, the weighted average value for polarity can be between -1 and 1 where the tweets with negative polarities mean negative sentiments while the tweets with positive polarities equate to positive sentiments. The subjectivity value can be between 0 and 1. Subjectivity quantifies the amount of opinion and facts or information contained in the text. The higher subjectivity means that the text contains opinion rather than facts or information.
5. **GARCH Model**

we employ a GARCH (1,1) model with robust standard errors, utilizing the conditional mean equation (eq. 1) and the conditional variance equation (eq. 2) on the 6 indices. Our dependent variable is daily index returns, and our main independent variables is the polarity, our control variables are lagged daily change in interest rates and lagged daily change in inflation rates.

\[
Y^{\{1-5\}}: \text{ Daily log returns of the 6 global indices \{GSPC, DJI, IXIC, FCHI, DAXI & N225\}}
\]

\[
X1: \text{ COVID-19 polarity/ investor sentiment.}
\]

\[
X2: \text{ change in the US treasury bill rates.}
\]

\[
X3: \text{ change in US inflation rates.}
\]

As mentioned before, for each model our H0 or null hypothesis is that the investor sentiment based on the COVID-19 tweets polarity had no impact on the stock index volatility. Our H1 or Alternative Hypothesis is that the investor sentiment had an impact on the stock market volatility represented by each index.

H0: The Covid-19 tweets polarity had no impact on the stock index volatility.

H1: The Covid-19 tweets polarity impacted the stock index volatility.
**Model 1**

\[
GSPC = C(1) + C(2) \times GSPC(-1) + C(3) \times Polarity(-1) + C(4) \times IR_{90 Days}(-1) + C(5) \times Inflation \text{Rate}(-1) + [MA(1) = c(6), UNCOND, ESTSMP = 1/14/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-1) + C(11) \times IR_{90 Days}(-1) + C(12) \times Inflation \text{Rate}(-1)
\]

**Model 2**

\[
DJI = C(1) + C(2) \times DJI(-1) + C(3) \times Polarity(-1) + C(4) \times IR_{90 Days}(-1) + C(5) \times INFLATION \text{Rate}(-1) + [MA(1) = c(6), UNCOND, ESTSMP = 1/14/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-1) + C(11) \times IR_{90 Days}(-1) + C(12) \times INFLATION \text{Rate}(-1)
\]

**Model 3**

\[
IXIC = C(1) + C(2) \times IXIC(-1) + C(3) \times Polarity(-1) + C(4) \times IR_{90 Days}(-1) + C(5) \times INFLATION \text{Rate}(-1) + [MA(1) = c(6), UNCOND, ESTSMP = 1/14/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-1) + C(11) \times IR_{90 Days}(-1) + C(12) \times INFLATION \text{Rate}(-1)
\]

**Model 4**

\[
FCHI = C(1) + C(2) \times FCHI(-1) + C(3) \times Polarity(-2) + C(4) \times IR_{90 Days}(-1) + C(5) \times INFLATION \text{Rate}(-1) + [MA(1) = c(6), UNCOND, ESTSMP = 1/15/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-2) + C(11) \times IR_{90 Days}(-1) + C(12) \times INFLATION \text{Rate}(-1)
\]

**Model 5**

\[
GDAXI = C(1) + C(2) \times FCHI(-1) + C(3) \times Polarity(-2) + C(4) \times IR_{90 Days}(-1) + C(5) \times INFLATION \text{Rate}(-1) + [MA(1) = c(6), UNCOND, ESTSMP = 1/15/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-2) + C(11) \times IR_{90 Days}(-1) + C(12) \times INFLATION \text{Rate}(-1)
\]
Model 6

\[ N225 = C(1) + C(2) \times FCHI(-1) + C(3) \times Polarity(-3) + C(4) \times IR90_DAYS(-1) + C(5) \times INFLATION_RATE(-1) \\
+ [MA(1) = C(6), UNCOND, ESTSMP = 1/15/2020 12/21/2020] \]

\[ GARCH = C(7) + C(8) \times Resid(-1)^2 + C(9) \times GARCH(-1) + C(10) \times Polarity(-3) + C(11) \times IR90_DAYS(-1) \\
+ C(12) \times INFLATION_RATE(-1) \]
5. Results

This section analyzes the results of the estimated GRACH model that models the relation between each index log-returns and the independent variables: polarity, interest rate (control variable), and inflation rate (control variable). The estimates of the variance equation in the GARCH (1,1) model of each index are reported in tables 2, 3, 4, 5, 6 & 7 below. Our main results from GARCH (1,1) indicate that while the investors sentiment based on the COVID-19 tweets shows no significant effect on the returns of the developed markets indices, conditional heteroscedasticity tends to be affected, indicating an impact on volatility and trading volumes of the six developed market global indices. This indicates an impact of COVID-19 measured by the polarity of the covid-19 tweets on volatility and trading volumes of the six developed market indices.

This finding is in line with (Baker et al., 2020) who studied the COVID-19 news’ impact on stock market volatility for two months and (Onali, 2020) who studied the effect of the changes of the number of COVID-19 cases on the DJI and S&P500 indices. Baker et al. (2020) stated that all the covid-19 news whether positive or negative, acted as the main determinant of stock market movements from late February 2020 till early April 2020. They also stated that the frequency of large daily stock market moves during this period is exceptional. They explicitly stated that the COVID-19 period stands out for an extremely high frequency of large daily stock market moves, stressing that it never happened in the past 120 years that the development of a pandemic caused such market fluctuations or even drove any large daily stock market moves (Baker et al., 2020). Onali (2020) found that the changes in the number of cases and deaths related to Covid-19 drastically affected the volatility of the Dow Jones and S&P500. However, there is little evidence that they have had a significant effect on the stock returns (Onali, 2020).
S&P 500 (GSPC): our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. P-values less than 0.05 are an indicator of the significance of the model as they mean we can reject the Null hypothesis or H0. The Null hypothesis was that the investor sentiment caused by the COVID-19 has no effect on the volatility of the stock market index. P-values are all less than 0.05 for all independent variables except interest rate. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the S&P 500 volatility.

Table 2: Results of the S&P 500 (GSPC) GARCH Model

<table>
<thead>
<tr>
<th>Variance:</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.000045</td>
<td>0.0023</td>
</tr>
<tr>
<td></td>
<td>(0.0000148)**</td>
<td></td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.173053</td>
<td>0.0327</td>
</tr>
<tr>
<td></td>
<td>(0.081048)**</td>
<td></td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.521159*</td>
<td>0.0005</td>
</tr>
<tr>
<td></td>
<td>(0.148605)</td>
<td></td>
</tr>
<tr>
<td>Polarity(-1)</td>
<td>-0.000161*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000363)</td>
<td></td>
</tr>
<tr>
<td>IR_90_Days(-1)</td>
<td>0.000000717</td>
<td>0.9815</td>
</tr>
<tr>
<td></td>
<td>(0.00000309)</td>
<td></td>
</tr>
<tr>
<td>Inflation_Rate(-1)</td>
<td>0.0000313*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.00000785)</td>
<td></td>
</tr>
</tbody>
</table>

Observations: 225
R-squared: 0.126708
Adjusted R-squared: 0.106770
Durbin-Watson stat: 2.037693
Inverted MA Roots: -0.04

(1) Parentheses imply St. Error.
(2) *, ** indicate statistical significance at the 1%, 5% levels respectively.

The above was conducted using the following equation.

\[
\text{GSPC} = C(1) + C(2) \times \text{GSPC}(-1) + C(3) \times \text{POLARITY}(-1) + C(4) \times \text{IR}_{90_{\text{DAYS}}}(-1) + C(5) \times \text{INFLATION\_RATE}(-1) + [\text{MA}(1) = C(6), \text{UNCOND\_\_ESTSMPL} = "1/14/2020 12/21/2020"]
\]

\[
\text{GARCH} = C(7) + C(8) \times \text{RESID}(-1)^2 + C(9) \times \text{GARCH}(-1) + C(10) \times \text{POLARITY}(-1) + C(11) \times \text{IR}_{90_{\text{DAYS}}}(-1) + C(12) \times \text{INFLATION\_RATE}(-1)
\]
Dow Jones Industrial Average (DJI): our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. The P-value for the polarity independent variable (0.0009) which indicates the significance of the model as they mean we can reject the Null hypothesis or H0. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the Dow Jones volatility. That is, COVID-19 tweets polarity affected the Dow Jones volatility.

Table 3: Results of the Dow Jones Industrial Average (DJI) GARCH Model

<table>
<thead>
<tr>
<th>Variance:</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0000033(0.00000229)</td>
<td>0.1488</td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.425504**(0.147208)</td>
<td>0.0038</td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.547921*(0.103519)</td>
<td>0.0000</td>
</tr>
<tr>
<td>Polarity (-1)</td>
<td>0.0000634*(0.0000190)</td>
<td>0.0009</td>
</tr>
<tr>
<td>IR_90_Days (-1)</td>
<td>0.0000234(0.0000326)</td>
<td>0.4729</td>
</tr>
<tr>
<td>Inflation_Rate (-1)</td>
<td>-0.00000374(0.00000863)</td>
<td>0.6648</td>
</tr>
</tbody>
</table>

| Observations               | 225         |
| R-squared                  | 0.023702    |
| Adjusted R-squared         | 0.001412    |
| Durbin-Watsin stat         | 2.516875    |
| Inverted MA Roots          | -0.20       |

(1) Parentheses imply St. Error.
(2) *, ** indicate statistical significance at the 1%, 5% levels respectively.

The above was conducted using the following equation.

\[ DJI = C(1) + C(2) \cdot DJI(-1) + C(3) \cdot POLARITY(-1) + C(4) \cdot IR_{90\_DAYS}(-1) + C(5) \cdot INFLATION\_RATE(-1) + [MA(1) = C(6), UNCOND\_ESTSMP = "1/14/2020 12/21/2020"] \]

\[ GARCH = C(7) + C(8) \cdot RESID(-1)^2 + C(9) \cdot GARCH(-1) + C(10) \cdot POLARITY(-1) + C(11) \cdot IR_{90\_DAYS}(-1) + C(12) \cdot INFLATION\_RATE(-1) \]
Nasdaq (IXIC): Our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. The P-value for the polarity independent variable (0.0001) which indicates the significance of the model as they mean we can reject the Null hypothesis or H0. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the Nasdaq volatility. That is, Covid-19 tweets polarity affected the Nasdaq volatility.

Table 4: Results of the Nasdaq (IXIC) GARCH Model

<table>
<thead>
<tr>
<th>Variance:</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0000381*</td>
<td>0.0002</td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.202702**</td>
<td>0.0276</td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.497912*</td>
<td>0.0001</td>
</tr>
<tr>
<td>Polarity (-1)</td>
<td>-0.000139*</td>
<td>0.0001</td>
</tr>
<tr>
<td>IR_90_Days (-1)</td>
<td>-0.0000123</td>
<td>0.6545</td>
</tr>
<tr>
<td>Inflation_Rate (-1)</td>
<td>0.0000292*</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

| Observations | 225          |
| R-squared    | 0.111944     |
| Adjusted R-squared | 0.091669 |
| Durbin-Watsin stat | 2.225181 |
| Inverted MA Roots | -0.06       |

(1) Parentheses imply St. Error.
(2) *, ** indicate statistical significance at the 1%, 5% levels respectively.

The above was conducted using the following equation.

\[
IXIC = C(1) + C(2) \cdot IXIC(-1) + C(3) \cdot POLARITY(-1) + C(4) \cdot IR_{90\_DAYS(-1)} + C(5) \cdot INFLATION_{\text{RATE(-1)}} + [MA(1) = C(6), UNCOND, ESTSMPL = 1/14/2020 12/21/2020]
\]

\[
GARCH = C(7) + C(8) \cdot RESID(-1)^2 + C(9) \cdot GARCH(-1) + C(10) \cdot POLARITY(-1) + C(11) \cdot IR_{90\_DAYS(-1)} + C(12) \cdot INFLATION_{\text{RATE(-1)}}
\]
CAC 40 (FCHI): Our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. The P-value for the polarity when lagged at two days independent variable (0.0000) which indicates the significance of the model as they mean we can reject the Null hypothesis or H0. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the CAC40 volatility. That is, COVID-19 tweets polarity affected the CAC 40 volatility with a lag of two days in time. The two-days lag is due to reasons like the different time zones and the lead of the US stock markets (Leonidas, 2012) (Copeland et al., 1998) (Eum et al., 1989).

Table 5: Results of the CAC 40 (FCHI) GARCH Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0000262*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.00000557)</td>
<td></td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.288257**</td>
<td>0.0037</td>
</tr>
<tr>
<td></td>
<td>(0.099372)</td>
<td></td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.500072*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.086065)</td>
<td></td>
</tr>
<tr>
<td>Polarity (-2)</td>
<td>-0.000107*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000257)</td>
<td></td>
</tr>
<tr>
<td>IR_90_Days (-1)</td>
<td>0.00000943</td>
<td>0.7841</td>
</tr>
<tr>
<td></td>
<td>(0.0000344)</td>
<td></td>
</tr>
<tr>
<td>Inflation_Rate (-1)</td>
<td>-0.0000261*</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000535)</td>
<td></td>
</tr>
</tbody>
</table>

|                        | Observations:       | 224          |
|                        | R-squared:          | -0.032817    |
|                        | Adjusted R-squared: | -0.056506    |
|                        | Durbin-Watsin stat: | 2.100540     |
|                        | Inverted MA Roots:  | -0.02        |

(1) Parentheses imply St. Error.
(2) *, ** indicate statistical significance at the 1%, 5% levels respectively.

The above was conducted using the following equation.

\[ FCHI = C(1) + C(2) \cdot FCHI(-1) + C(3) \cdot POLARITY(-2) + C(4) \cdot IR_90_DAYS(-1) + C(5) \cdot INFLATION_RATE(-1) + [MA(1) = C(6), UNCOND, ESTSMPL = "1/15/2020 12/21/2020"] \]

\[ GARCH = C(7) + C(8) \cdot RESID(-1)^2 + C(9) \cdot GARCH(-1) + C(10) \cdot POLARITY(-2) + C(11) \cdot IR_90_DAYS(-1) + C(12) \cdot INFLATION_RATE(-1) \]
DAX (GDAXI): Our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. The P-value for the polarity when lagged at two days independent variable (0.0000) which indicates the significance of the model as they mean we can reject the Null hypothesis or H0. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the DAX volatility. That is, COVID-19 tweets polarity affected the DAX volatility with a lag of two days in time. The two-days lag is due to reasons like the different time zones and the lead of the US stock markets (Leonidas, 2012) (Copeland et al., 1998) (Eum et al., 1989).

Table 6: Results of the DAX (GDAXI) GARCH Model

<table>
<thead>
<tr>
<th>Variances:</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.0000370*</td>
<td>0.0001</td>
</tr>
<tr>
<td>(0.00000912)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.215715**</td>
<td>0.0154</td>
</tr>
<tr>
<td>(0.089013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.490694*</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.099690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Polarity (-2)</td>
<td>-0.000128*</td>
<td>0.0000</td>
</tr>
<tr>
<td>(0.0000291)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IR_90_Days (-1)</td>
<td>0.00000590</td>
<td>0.7917</td>
</tr>
<tr>
<td>(0.0000224)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflation_Rate (-1)</td>
<td>-0.0000370**</td>
<td>0.0030</td>
</tr>
<tr>
<td>(0.0000124)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

|                      |                   |              |
| Observations         | 224               |              |
| R-squared            | -0.018691         |              |
| Adjusted R-squared   | -0.042055         |              |
| Durbin-Watsin stat   | 1.888786          |              |
| Inverted MA Roots    | 0.01              |              |

(1) Parentheses imply St. Error.
(2) *, ** indicate statistical significance at the 1%, 5% levels respectively

The above was conducted using the following equation.

\[
GDAXI = C(1) + C(2) \times PCHI(-1) + C(3) \times POLARITY(-2) + C(4) \times IR_90_DAYS(-1) + C(5) \times INFLATION\_RATE(-1) + [MA(1) = C(6), UNCOND, ESTSMPL = "1/15/2020 12/21/2020"]
\]

\[
GARCH = C(7) + C(8) \times RESID(-1)^2 + C(9) \times GARCH(-1) + C(10) \times POLARITY(-2) + C(11) \times IR_90_DAYS(-1) + C(12) \times INFLATION\_RATE(-1)
\]
Nikkei 225 (N225): Our GARCH (1,1) model shows that the coefficients sum up to a number less than one which is required in order to have a mean reverting variance process. The P-value for the polarity when lagged at three days independent variable (0.0022) which indicates the significance of the model as they mean we can reject the Null hypothesis or H0. Therefore, we reject the null hypothesis that the COVID-19 tweets polarity has no impact on the Nikkei 225 volatility. That is, COVID-19 tweets polarity affected the Nikkei 225 volatility with a lag of three days in time. The three days lag is due to reasons like the different time zones and the lead of the US stock markets (Leonidas, 2012) (Copeland et al., 1998) (Becker et al., 1992)

Table 7: Results of the Nikkei (N225) GARCH Model

<table>
<thead>
<tr>
<th>Variance</th>
<th>Variable</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td>0.0000238*</td>
<td>0.0078</td>
</tr>
<tr>
<td></td>
<td>(0.00000896)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>RESID(-1)^2</td>
<td>0.166144**</td>
<td>0.0157</td>
</tr>
<tr>
<td></td>
<td>(0.068767)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>GARCH(-1)</td>
<td>0.532103*</td>
<td>0.0005</td>
</tr>
<tr>
<td></td>
<td>(0.151954)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Polarity (-3)</td>
<td>-0.0000961*</td>
<td>0.0022</td>
</tr>
<tr>
<td></td>
<td>(0.0000314)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>IR_90_Days (-1)</td>
<td>-0.00000224</td>
<td>0.9269</td>
</tr>
<tr>
<td></td>
<td>(0.0000245)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Inflation_Rate (-1)</td>
<td>-0.0000299*</td>
<td>0.0030</td>
</tr>
<tr>
<td></td>
<td>(0.00000219)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>223</td>
<td></td>
</tr>
<tr>
<td></td>
<td>R-squared</td>
<td>0.024327</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Adjusted R-squared</td>
<td>0.001846</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Durbin-Watsin stat</td>
<td>1.885050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Inverted MA Roots</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

Table 7: Results of the Nikkei (N225) GARCH Model

The above was conducted using the following equation.

\[
\begin{align*}
N225 &= C(1) + C(2) \cdot FCCHI(-1) + C(3) \cdot POLARITY(-3) + C(4) \cdot IR_90\_DAYS(-1) + C(5) \cdot INFLATION\_RATE(-1) \\
&+ \text{MA}(1) = C(6), \text{UNCOND, ESTSML} = \text{1/15/2020 12/21/2020} \\
GARCH &= C(7) + C(8) \cdot RESID(-1)^2 + C(9) \cdot GARCH(-1) + C(10) \cdot POLARITY(-3) + C(11) \cdot IR_90\_DAYS(-1) \\
&+ C(12) \cdot INFLATION\_RATE(-1)
\end{align*}
\]
6. Conclusion

1. Conclusion

The thesis examines the relation between investor sentiment based on the COVID-19 tweets and six developed markets indices in terms of returns and volatility. The results of our thesis confirm that the investors sentiment based on the COVID-19 tweets shows significant impact on the conditional heteroscedasticity of the developed markets indices, indicating an impact on volatility and trading volumes of the six developed market indices. Our findings are consistent with the previous work of Baker et al. (2020). Baker et al. (2020) argue that during the month of March 2020, the market jumps surpassed any period in the past with comparative number of trading days. They also state that all the COVID-19 news whether positive or negative, was the main determinant of stock market movements from late February 2020 till early April 2020. Our findings are also consistent with Onali (2020); the changes in the number of cases and deaths related to COVID-19 drastically affected the volatility of the Dow Jones and S&P500, but there is little evidence that they have had a significant effect on the stock returns.

Our results show the that the COVID-19 tweets had an impact on the stock markets volatility on the following day (with one day lag) for the US indices (S&P 500, Dow Jones Industrial Average and Nasdaq). Nonetheless, the impact on the CAC40 and DAX velocity was evident with two days lag and three days lag in case of Nikkei 225. This lag can be further explained by different time zones, and different trading hours.

Notwithstanding, the drastic stock market panic caused by the COVID-19 pandemic, other factors played a role in the stock market volatility during FY20. The oil market has had volatility that cannot just be explained by the COVID crisis, as oil prices dropped in late April 2020, with West Texas crude dropping below zero on the 19th April 2020 (Damodaran, 2020). The US presidential elections and subsequent events had a definite impact on stock movements and returns worldwide. The policies undertaken by most of the governments around the world including quantitative easing and the economic relief and stimulus packages like the US economic relief programs and the subsequent fiscal stimulus package announced in March 2020, might have pushed the stock market upwards and decreased volatility expectations.
2. Implications And Further Research

The existing literature has established the relationship between news and social media platforms on investors' sentiment and, subsequently stock market. However, the literature reveals that not many studies have been carried out regarding measuring volatility during pandemics, especially the COVID-19 pandemic. Furthermore, although studies are tackling the effect of COVID-19 news on investors' sentiment and the stock market, no adequate studies are utilizing the Twitter platform and Tweets as a driver of investors’ sentiment. In addition, no studies are analyzing the investors’ sentiment impact on stock markets globally and how the dissemination of information and opinions through the Twitter platform affected volatility and returns across the developed markets worldwide. Therefore, this paper will attempt to fill the gap in the literature and try to address how accurately COVID-19 Twitter posts were able to model the movement and volatility of stock markets globally.

Our thesis can serve as the base for further research and studies in the field of sentiment analysis and stock market performance, especially in relation to the ongoing COVID-19 pandemic. Our thesis covered the period from the 4th of January 2020 till the 21st of December 2020, which is almost the whole year of 2020. Further prolonged study period can cover the 2020 and 2021; analyzing COVID-19 tweets maid the vaccination and re-opening era and studying the effect of such tweets on investors’ sentiment and subsequently stock market returns and volatility. Furthermore, our thesis relied on macroscopic daily returns of the six indices under the study. Given that Twitter is a real-time platform for disseminating information and opinions, the investors’ sentiment can be analyzed per second or even millisecond using tweets. Thus, a study assessing the relationship of investors’ sentiment based on tweets per second and microscopic “tick by tick” stock returns would be interesting and valuable. In addition, our methodology for sentiment analysis relied on unsupervised machine learning utilizing pre-defined lexicons. Given the novelty and exclusivity of the COVID-19 pandemic; using supervised machine-learning by training a data set on the specific COVID-19 key words can result in enhanced results. Last but not least, expanding the research to cover more indices representing developed and developing markets would give a new perspective and a more comprehensive picture.
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