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The impact of Twitter on financial stability

A DISSERTATION SUBMITTED FOR THE DEGREE OF XXX

Abstract

Twitter has a substantial impact on market volatility, investor sentiment, business reputation, and financial regulation. The objective of this investigation is to investigate the impact of investor sentiment on financial stability by analysing the stock prices of Apple and investor sentiment. The majority of the tweets from Apple are neutral, according to an autonomous manual analysis. The quantity of positive tweets surpasses that of negative tweets. Negative tweets pertain to an absence of innovation, insufficient updates, excessive expenditure, dissatisfaction, inflated pricing, inadequate leadership, and stock buybacks, as well as revenue loss. Profit, revenue per employee, quality products, record revenue/sales, innovation, and expansion are all topics that are associated with favourable tweets. The researcher initially conducted an uncomplicated regression analysis using the dependent variable (stock price percentage change) and the independent variable (sentiment index). The asset price shifts by only 0.014 units for each one-unit increase in the sentiment index. Despite the use of a window view, certain intervals demonstrate a significant relationship between the variables, while others lack evidence relating the sentiment index to stock price fluctuations. This research demonstrates that investor sentiment has a weak direct impact on asset prices. It is possible to acquire insights into the manner in which the firm is represented online and the extent to which investors' awareness of such sentiment influences their decisions by comprehending the potential relationship between sentiment and stock performance.

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Chapter One: Introduction

1.1. Background to Research Topic

The rise of internet activity, including the generation of huge data sets, has created opportunities for academics and practitioners in diverse fields to understand the impact of the 'big data' revolution on various factors. This includes the impact on financial stability (Gakhar and Kundlia, 2021). This dissertation intends to understand if investor sentiment, evaluated through social media behaviour, can be useful to understand ongoing developments within financial markets. The financial sentiment literature indicates that diverse outcomes, including macro-economic announcements (Banchit et al., 2020), geopolitical events (Guo and Shi, 2024) and corporate announcements (Mahmoudi et al., 2022), can have an impact on investor sentiment and eventually influence stock prices and firms' financial stability. While, in the past, such investor information was gained from traditional mainstream sources like analyst research reports, financial news, newspapers and official announcements, there has been a shift towards more digital media-driven communication. For example, Gan et al. (2020) contended that there is a rise in companies using their website to share financial information, including annual and quarterly reports as well as future financial forecasts and projections. There is also a rise in the use of social media platforms like Twitter and StockTwits acting as instant channels to share integrated stock information (Seetharam and Nyakurukwa, 2024). The use of social media as a tool for the dissemination of data impacting investor outcomes has been discussed by scholars. For example, there is evidence of organisations using social media channels such as Twitter to disseminate news about earnings and other corporate announcements, with the goal of reducing information asymmetry (Albarrak et al., 2020). Guest (2021) similarly contended that the sharing of news on social media by corporations themselves can be a way to reach a broader audience base. However, there is evidence to show that firms may be looking at social media platforms as an opportunistic tool to convey information that is mostly positive.

Apart from organisation-initiated information, there are other sources of data available to investors on social media. These include views by financial experts who provide online discussion forums, blogs and other educational material (Valle-Cruz et al., 2022). For example, Bloomberg, a financial expert and news organisation, has added Twitter accounts to its financial information terminals. There are also regulators who recognise the importance of social media. The US Securities and Exchange Commission (SEC) has issued guidance asking for firms to ensure the use of digital media, including corporate tools, to provide information to investors and consumers (Gakhar and Kundlia, 2021). Furthermore, as Bartov et al. (2018) indicated, the SEC allows small firms that are looking to become public to look at social media platforms, including Twitter, as a way to gauge potential interest from investors. Additionally, there are investors who engage in discussions to gain information on shifts in stock market trends. These investors consider social media a collaborative pool of knowledge for investment on stock markets (McGurk et al., 2020). Extant literature also argues that social media is a way to provide insights into market sentiment and the behaviour of investors (Affuso and Lahtinen, 2019) and is a market sentiment indicator (Yang and Mo, 2016). The proposed analysis will evaluate behavioural finance-related outcomes for firms as it provides real-time and accurate sentiment analysis. All of the evidence supports the argument that use of social media platforms could act as a potential influencer impacting investor sentiment and thereby influencing the financial stability of firms.

As a well-known social media site, Twitter enables its users to communicate with a worldwide audience through the sharing of brief messages known as tweets. Evidence suggests that Twitter significantly impacts market volatility, investor sentiment, business reputation and financial regulation, among other components of financial stability. Nevertheless, a thorough and organised examination of this subject is lacking, and current research on the effects of Twitter on monetary stability is scant and incomplete. This dissertation seeks to address this knowledge vacuum by investigating the effects of Twitter on financial stability and considering the implications of the findings for policy and practice.

1.2. Rationale and Motivation of Research

The use of social media applications as communication tools can provide a significant amount of information to both investors and analysts. Therefore, it becomes essential for firms to understand their role in contributing to financial performance and stability (Camargo and Dantas, 2023). The use of these tools is expected to significantly change how firms manage their investors and, more importantly, how firms look to share information regarding their earnings, strategic actions and other important information (Al Atoom et al., 2021). Diverse opinions are shared through social media platforms. A key strength of messages gained through social media platforms is that they are uncorrelated and therefore represent a range of views rather than those given through an organisation's official channels (Chahine and Malhotra, 2018). Information about a firm obtained through social media may have an incremental impact on stock ratings. Gu and Kurov (2020) believe that daily assessment of Twitter sentiments may influence daily analyst ratings, which is indicative not just of investors but also of experts gathering information from social media platforms. Investors on social media have the ability to transform from being passive recipients of information to active stakeholders who communicate, comment, mention and share information regarding an organisation's activities (Chahine and Malhotra, 2018). According to Coelho et al. (2019), such actions have a potential positive influence on the diffusion of information. However, a challenge that exists is that not all information is positive and wrong or uncorroborated information can be shared on social media (Shiller, 2000). Financial markets are largely driven by expectations and investors may buy or sell shares as a result of sentiments impacting fear or desire for some event (Ramassa and Di Fabio, 2016). Investors look to media credibility in the past. However, the use of online social media platforms like Twitter, Facebook and Instagram has created challenges in establishing such credibility given the large volume of information (Cooley and Arks-Yancy, 2019).

The advent of social media has introduced a new factor, however—the speed with which everything happens, which might magnify market sentiment. Chen, De, and Hu (2014) investigated the ways in which social media might foretell market trends and mirror the sentiments of numerous users. By democratising access to financial data, social media platforms can increase market transparency. On the other hand, they have the ability to spread misinformation, which could lead to unexpected market movements. A recent example of how social media has the potential to shake up large financial markets and cause instability is the 2021 GameStop short squeeze (Corbet et al., 2021). Posts on traditional broadcasting platforms on topics that are popular on social media can influence market sentiment and investment choices because of the interplay between the two types of media (Perkins, 2020).

In this context, there can be diverse behavioural responses from investors which can contradict the notion of market efficiency. Methodologically, a challenge is that it can be difficult to empirically observe and evaluate all forms of investor behaviour (Drobetz et al., 2019). One approach that has been relevant in the past is the concept of social media sentiment analysis. Social media information can be used to identify the investor sentiment index as a potential proxy where all types of information (positive, negative and passive) are assessed (Bukoniva, 2016). This has been a primary factor behind why there is scrutiny of information and sentiment sharing from social media platforms in diverse contexts. This research intends to contribute to this evolving research to understand investor sentiment and its influence on financial stability through an examination of Apple's stock prices and investor sentiment.

In this study, the researcher chose Apple as the target organisation. Apple, a global technology company, was chosen as it has an active social media presence. It is one the most innovative firms in the world and its performance is closely monitored by investors. The brand has a large and loyal customer base who may engage with the organisation's social media handles. Apple's innovative product launch, earnings reports and media coverage are some aspects that may create discussion on social media platforms, which may influence investor sentiment.

1.3. Research Questions and Research Objectives

The primary research question of this study is:

What impact does public sentiment on Twitter (measured through sentiment analysis) have on stock price performance and the financial stability of target firms?

To answer this question, there are key objectives.

a. To conduct a sentiment analysis of target corporation's tweets to arrive at the sentiment index through the categorisation of positive, negative and passive tweets.
b. To examine the impact of this sentiment index on the firm's stock price performance.
c. To provide recommendations to corporations and financial analysts on the role of social media sentiments in decision-making.

1.4. Expected Results: Business Significance

Since its introduction in 2006, Twitter has developed into one of the world's most prominent and widely used social media networks. Actors, politicians, celebrities, journalists and investors have all made extensive use of Twitter to voice their thoughts and shape public debate. Journalists, researchers and analysts in the financial industry rely on it for reporting and analysing breaking financial news and for providing insights and predictions on a range of financial topics and trends (Pagolu et al., 2016). Therefore, Twitter is an important tool that influences investor analysis.

Investor behaviour and prediction has been a challenging problem impacting researchers and analysts (Hanlon et al., 2022). According to Al Guindy (2021), the complexity of the financial system is linked to contagion effects of the impact of diverse stakeholders. The rise in information made available to investors through social media platforms can change the pattern of investors' behavioural reactions. Since investor attention is a limited cognitive resource, and since not all of the public release of information is actually understood and accessed by investors, the presentation and medium of information gathering is important and can influence overall investor decisions (Nekrasov et al., 2022). Through this research, the aim is to evaluate the degree to which sentiments expressed on social media may have an anticipatory impact on investor behaviour. The study intends to identify if there is an established relationship between sentiment index and stock return. If there is a positive relationship—i.e. the sentiment index has an influence on higher stock returns and if negative sentiment leads to lower stock returns—then there is an established relationship between the variables. By understanding the potential relationship between sentiment and stock performance, it is possible to gain insights into how the firm is represented online and the extent to which investors' awareness of such sentiment impacts their decisions. Through this analysis, there can be implications for businesses to better anticipate market reaction to evolving public sentiment in order to manage their communication. On the other hand, sentiment analysis can influence policy decisions. This can include policies and regulations regarding the publication of information online. If policymakers better understand how sentiment influences potential market shifts, it is possible to create informed regulations with the goal of protecting investors.

1.5. Overview of the Dissertation

This dissertation is organised in five chapters. Chapter Two presents the study's literature review. The chapter presents the theoretical basis of the study along with prior empirical literature that addresses similar study. Chapter Three presents the study methodology with a focus on the research design, data collection and data analysis. Chapter Four presents the study findings and revisits the study hypotheses, while Chapter Five concludes the study by presenting the study conclusion and recommendations.

Chapter Two: Review of Literature

2.1. Introduction

The purpose of this chapter is to present the review of literature of the study. The chapter provides a discussion on the theoretical and emprical literature on the chosen research subject. The researcher targeted academic databases including Sage, Springer Link, ScienceDirect, JSTOR, SSRN, Wiley Online and Emerald Insight to identify relevant articles. The following search terminology was used.

("Investor Sentiment" OR "Market Sentiment") AND ("Stock Price" OR "Stock Price Movements" OR "Stock Market Performance") AND ("Impact" OR "Effect")

2.2. Theoretical Basis

2.2.1. Investor Sentiment Analysis

The fluctuation of asset prices is largely impacted by the degree of access to information. When a specific event occurs (either internal or external), markets and investors may change or adjust their expectations about the price of the asset (Shanmugasundaram, 2011). When there are high expectations, there is high demand for the asset, influencing both institutional and individual investors (Pradana and Vanomy, 2020). High expectations and demand for the asset could mean that investors react by selling or buying the asset. Investor sentiment is conceptualised as investors' expectation of the future price of the asset, which can impact their willingness to buy or sell the asset (Park et al., 2014). New information can change or impact investor sentiment and new investor sentiments impact new prices (Yang and Wu, 2021). Therefore, sentiment is characterised as an important factor that impacts the market.

Sentiment as a factor impacting investors' decision-making was neglected during the early stages of traditional financial theory. Keynes' (1936) seminal research acknowledged that sentiment is a factor influencing market-related outcomes, contending that economic activity is governed by factors including the spirit and sentiment of individuals and calling for a focus on sentiments and speculative markets. However, since then, other authors have questioned the relevance of sentiment theory to market impact (Aggarwal, 2022). This scepticism was attributed to evolving challenges linked to real investor sentiment analysis and associated challenges. Sentiment was found to be difficult to measure as there were no reasonable indicators by which to make the assessment (Zhou, 2018). Modern financial theories that took into account the importance of information and its relevance and impact on the market did not talk about the importance of sentiment. In particular, the efficient market hypothesis (EMH) proposed by Fama (1970) is discussed in this research.

The EMH in financial economics holds that asset prices are able to reflect all information. The theory contends that markets are efficient and market participants exhibit rational risk aversion. The information efficiency of the market is such that there is no room for participants to outperform the market (Fama, 1965). The EMH is considered one of the most important milestones in the history of finance theory, Wen-Chen and Ku-Jun (2005) having been cited more than 40,000 times in the last two decades. The theory holds that information can predict asset price under ideal conditions. However, multiple studies have since argued that there are multiple inefficiencies within the EMH and that factors including behavioural financial elements need to be considered. For example, Peon et al. (2019) contended that the classic theory does not explain the presence of systematic mispricing, which may arise as a result of sentimental factors. Additionally, as Zhou (2018) contended, misinformation and noise leading to panic or mania cannot be explained effectively by the EMH.

To address this limitation, the concept of behavioural finance evolved in the 1980s and has since expanded extensively (Angeles Lopez-Cabarco et al., 2020). This theory holds that it is important to evaluate market asset prices by considering the psychological perspective of stakeholders (Raissi and Missaoui, 2015). Behavioural finance scholars evaluated violation of the EMH in relation to investor sentiments (Kumar, 2019). There has been research to show that investor sentiment can cause potential deviations in the price of the asset from the fundamental value (Shiller, 1984; Shleifer and Vishny, 1997). De Long et al. (1990) serve as just one example of how researchers record the effects of illogical behaviour of investors, where they take into account the challenges identified by investors. In their approach, the authors distinguished between 'noise traders' and 'rational traders' as two types of investor. Sias et al. (2001) identified noise traders as those who invest in the stock market on the basis of sector affinities rather than basic trading factors. Noise traders' erratic investing strategies generate market movements, which they then use to manipulate fund prices via methodical forecasting. For instance, if these traders' negative outlook on their prospects causes them to sell their funds, the cost of funds will fall under the value of their net assets (De Long et al., 1990, p. 161). This lends credence to Kyle's (1985) and Black's (1986) original idea that investors would rather trade on 'noise' than on basic variables or logical decision-making when selecting stocks. Such evidence proved that the old econometric model was missing important human characteristics that make an investor successful. According to Fernandes et al. (2013), a large number of investors make decisions based on data rather than price, which affects the values of assets, specifically shares.

An evaluation of the behavioural finance literature shows that understanding the complexities of investor needs and investor sentiment can be challenging. For example, as Baker and Wurgler (2007) contended, everyone knows that the asset price is just the sum of all the purchasing and selling that investors do in reaction to market conditions. According to Woolridge and Snow (1990), investors' reactions are contingent upon their projections of the value of various financial assets in the years to come. An individual is more likely to purchase or hold an asset if they have optimistic expectations for it. On the other hand, if the individual is pessimistic, they might decide to sell it or not keep it. According to Raissi and Missaoui (2015), the asset price thus serves as a proxy for the general mood of investors.

An intricate process goes into the establishment of investor sentiment. Exogenous and endogenous variables work in tandem to boost genuine sentiment among investors. Diverse factors can influence investor sentiment, including public announcements (e.g. annual returns, earnings announcements) (Livnat and Petrovits, 2009), social events (e.g. FIFA World Cup, Olympics), political campaign and election results (Vieira, 2012), fake news (Brans and Scholtens, 2020), and external factors like the COVID-19 pandemic. These are all examples of exogenous sentiment-drivers. In addition, internal sentiment drivers need to be examined in detail (Zhou, 2018). According to Clarke et al. (2020), there are several factors that influence people's emotions: prejudice and faulty judgement, inattention, arrogance, unmet wants and desires, and other personal differences. As a result, even when given the same information, different investors may arrive at different conclusions. This is on top of the fact that, in the actual market, investors are constantly dedicated to uncovering new, supplementary information beyond what is commonly known and publicly available.

The EMH is reasonable because information is the main component that influences investor mood, which is why information is the driving force behind asset price fluctuations (Tripathi and Dixit, 2020). However, as we have seen, information is not the only element that influences investor attitude. This is the most plausible explanation for results that contradict the EMH, including various oddities and the shocking financial realities of bubbles and crashes (Van Eyde et al., 2023). In particular, asset prices in financial markets reflect the fact that investors' expectations are subject to change in response to the arrival of novel data, whether those investors are large institutions or individuals. Investors' expectations could shift in a number of different ways when faced with the same common information or occurrence. The following section addresses the assessment and measurement of investor sentiments.

2.2.2. Measuring Investor Sentiments

According to Dickinson and Hu (2015), sentiment analysis, also referred to as opinion mining, is an evolving field of research wherein there is analysis of the opinions of individuals, their sentiments and views, and their attitudes and emotions. The use of sentiment analysis is evolving: it can provide information on individuals' attitudes towards events, topics, products, leaders, service provision and organisations (Ma et al., 2021). The rise of information available online, including the volume and speed of data creation, has created more information on individuals' sentiments. This section intends to identify the role of sentiment analysis in defining the needs of individual stakeholders.

The evidence has led to decisions on understanding investor sentiment and ways to analyse investor sentiment. According to extant literature (Ma et al., 2021), a popular solution is the survey-based measure, where there is direct quantification of investors' sentiment. Secondly, there is acceptance of using textual or search-based methods to assess publications like newspapers and online forums to evaluate sentiment. This was introduced in the seminal research by Tetlock (2007), who indicated that, given the large amount of published data available, these indices can be used along with surveys. Thirdly, more focused market-based indices are created by sentiment relevant proxies: these are intended to assess the sentiment component from a specific set of observable factors.

According to Man et al. (2019), the use of surveys for sentiment analysis is popular. The purpose of the survey is to evaluate how investors foresee the direction of the stock market and the overall economy. Another way to do this is to develop the BW index, proposed by Baker and Wurgler (2006). Literature has demonstrated that this index can successfully predict future returns for small, distressed and extreme growth funds. According to some studies (Baker and Wurgler, 2006; Bu et al., 2023), the BW index can be used to predict investor sentiment and thereby understand asset pricing by using market-based proxies. On the other hand, there are others (e.g. Huang et al., 2015) who identify that the BW index does not statistically present the right outcomes for aggregate stock market returns when examined from a time-series perspective. Since then, other indices have evolved to assess investor sentiments. These include the FEARS index (Da et al., 2015) and consumer confidence index (Bathia and Bredin, 2013).

2.3. Empirical Analysis: Twitter Sentiment Analysis and Influence on Firm

Different empirical studies evaluate the direct impact of Twitter sentiment on firm performance. This section summarises some of these studies.

2.3.1. Impact of Sentiment on Twitter and Influence on Firm Performance

There are diverse studies linking Twitter sentiments to overall firm performance. The impact of social media interaction on a company's bottom line has been the subject of several studies. Because they facilitate easy and rapid communication between investors, analysts and corporate leaders, social media sites like Twitter have grown in importance in the world of finance. Here we will take a look back at some of the research that has considered how social media, specifically Twitter, affects stock prices and overall financial stability. The study by Chen et al. (2014) demonstrated the usefulness of investing-focused social media platforms as low-cost resources for stock market research and the dissemination of company-specific information. A different study by Chen et al. (2014) found that chief financial officers and chief executive officers who are active on social media sites like Facebook, LinkedIn and Twitter can help spread news about their companies more widely in the financial markets. This, in turn, gives these executives more power to pursue their personal agendas. The research by Ren et al. (2021) looked at the frequency of emotionally charged words in internet reviews to determine the strength of the emotions. Their research showed that the amount of emotion expressed in internet reviews has a substantial impact on product sales. A strong emotional investment in a topic may play a significant role in attracting attention, perhaps prompting people to seek out better informed sources of information. The correlation between consumer behaviour, information-seeking behaviours and internet sentiment is evident here. One interpretation is that the growing polarisation of opinion on social media on a popular subject strengthens the bond between online news consumption and more conventional news consumption practices. There is a stronger correlation between social media engagement and news website visits when both the amount of attention to sentiments from social media posts and the intensity of emotions grow. It therefore stands to reason that social media and online sentiment influence not only consumer behaviour but also investment behaviour, which in turn influences stock markets.

There are studies that evaluate the impact of specific Twitter moods on the stock market through a focus on sentiment analysis. For example, Bollen et al. (2011) analysed the textual data of daily Twitter feeds using two mood tracking tools (Opinion Finder, Google -Profile of Mood States tracker). The tools identified positive and negative moods, as well as dimensions of mood (calm, alert, sure, vital, kind and happy). The authors used a Granger causality analysis and a self-organising fuzzy neural network to investigate the impact of mood, concluding that there is a relationship between mood valence and its influence on individual behaviour and decision-making with regard to investments. In another study, Fekrazad et al. (2022) evaluated the link between social media sentiment and tweet sentiment. They observed outcomes at hourly and daily intervals. The authors identified that a higher proportion of negative tweets about an organisation within an hour/day leads to lower returns. They also found a higher short volume of stock, even if controlled for traditional media news sentiment. The authors contended that social media sentiment includes signals that extend beyond those found in traditional media, and understanding the valence of these relationships is important. In another study, Sul et al. (2014) compared Twitter posts from firms in the S&P 500 and analysed their cumulative emotional valence against the firms' stock returns. The emotional valence of tweets was found to impact stock outcomes. The authors acknowledged that the emotional valence of tweets from users with more followers had a stronger impact on same day returns.

2.3.2. Impact of Sentiments and Influence on Asset Price

There are many studies that argue that there is a link between sentiments on Twitter and stock prices. Kretinin et al. (2018) retrieved the 2017 annual data of 100 stocks chosen using screening tools. They found tweets about the chosen stocks the day before, the day after, and on the fluctuation date, and then narrowed the stocks down based on intriguing volumes or swings. There was a decent correlation between the attitude expressed in tweets and the price movements of the four equities that were considered for the study. Repeated tweeting by the same user, using all capital letters, using strong and emphatic language, maintaining a relatively lengthy tweet length and word count, and responding aggressively to other users' posts are all signs of dominance and submission seeking behaviour.

In another study, Chen and Dong (2023) evaluated tweets relating to Apple, Google, Microsoft and Netflix and conducted a sentiment analysis to evaluate their relationship with current and future stock prices. The authors first conducted a regression analysis where the sentiment score was independent and stock price was dependent. Actual stock price was found to be linked to shifts in sentiment. Furthermore, a decision tree approach was used to predict stock prices. When a decision tree-based analysis was carried out, there was evidence of improved prediction of stock price. Stock price movement and reflection of investor sentiments are found to be predicted by decision tree methods. For example, in the case of Apple, tweets with high scores for anticipation, surprise and trust and low scores for fear, anger and negative sentiment were found to bring about an increase in stock price. In another study, the impact of sentiment and geography on stock returns was evaluated. According to Affuso and Lahtinen (2019), Twitter sentiment, calculated by direct measures from Twitter posts, was compared against stock returns. The findings showed that Twitter sentiment is an important factor impacting stock returns and that Twitter investor sentiment had more influence in specific geographies. The findings showed that negative tweets had a much greater impact than positive tweets. The direct effect of sentiments was found to be economically significant at 0.036 and 0.078 for positive and negative sentiments, respectively.

A more generic lexicon-based sentiment analysis was carried out by Gakhar and Kundlia (2021). Their study attempted to predict stock characteristics including returns, volatility and liquidity. The study attempted to evaluate the impact of Twitter sentiment (positive, negative, directional and total). The study contradicts the views of Zhang et al. (2018), indicating that positive tweets have more impact than negative tweets on stock performance. The results showed that stock returns and volatility can be better predicted by favourable attitudes on Twitter than by liquidity. Instead of stock returns, negative sentiment ratings are a strong indicator of liquidity and volatility. Posting volume, or the overall number of tweets, was determined to have a substantial impact on all stock market indicators. In particular, sustainability and green marketing indicators had a significant positive influence. Companies that engage with environmentally friendly investments should stay active on social media sites like Twitter to uphold their corporate image and increase social value, as the research shows that investors who put money into these businesses often monitor their corporate social media accounts. Therefore, corporate level tweets are considered to be more important than individual investor sentiments.

The impact of volume is also discussed by Duz Tan and Tas (2021). Using firm-specific Twitter sentiment and activity, Duz Tan and Tas (2021) examined the influence of social networking sites in emerging countries, the United States and Europe from the viewpoint of international investors. The research showed that emotion and activity on Twitter affect profits and trading volume and can even forecast the amount of trading the day after. The researchers discovered that even after accounting for the general news sentiment, firm-specific sentiment on Twitter can be a useful predictor of stock returns. The authors concluded that across diverse geographical locations there is a significant positive influence of Twitter sentiment on market performance with influence on trading volume and return. However, across all markets, small firms are difficult to appraise and emerging market companies have high levels of information asymmetry.

2.3.3. Sentiment Analysis: Role of Specific Events and Role of Specific Stakeholders

There are studies that evaluate the notion of specific events and related actions and their influence on the stock market. For example, Valle-Cruz et al. (2022) evaluated the implications of financial sentiment analysis from the perspective of a pandemic. Through a focus on Twitter during the COVID-19 pandemic, the study intended to evaluate the impact of polarity in tweets on global financial indices through sentiment analysis. The research focused on influential financial expertise-related Twitter accounts (i.e. analyst accounts). The study calculated the polarity between financial market indices and posts on Twitter through the application of a date shift on tweets. Correlation analysis of indices performance days before and after the existing post was also carried out. The findings concluded that the market reacted between zero and ten days after important information was shared and disseminated during the COVID-19 pandemic. During the H1N1 pandemic, the impact was between zero and fifteen days after the information was shared. Twitter posts from important financial stakeholders including *New York Times*, Bloomberg, CNN News and Investing.com had the most impact on stock market behaviour. Valle-Cruz et al. (2022) called for targeted lexicon-based analysis with a focus on analysts' views.

Dhar and Bose (2020) also assessed the impact of emotions in Twitter communication and the influence on stock prices. The authors extracted emotional content from 189,303 tweets including financial data for six quarters for 105 companies listed on the NYSE from Fortune 1000 companies. The analysis showed a moderate effect of the pandemic crisis as reflected through sentiment analysis. According to their findings, during the COVID-19 pandemic, organisational Twitter usage increased significantly. There was a corresponding rise in the prevalence of both positive (joy) and negative (angry, fearful, sad) emotions. Additional research revealed that during the crisis, tweets expressing happiness were much lower in number, while tweets expressing despair were significantly higher. There was no discernible uptick in the negative emotion ratings of dread and rage per tweet. The results demonstrated a favourable correlation between tweet volume and the price of stocks. There was a strong correlation between the number of tweets and stock price even throughout the crisis. After accounting for organisational size, Twitter account age and Twitter follower count, this association was still statistically significant.

Another analysis during the COVID-19 pandemic saw Smith and O'Hare (2022) evaluate CEO tweets and their impact on financial markets. In this paper, the authors looked at the data from a time span that included the SARS-COV-2 pandemic to see if the daily news sentiment of various companies and the sentiment from their CEOs on Twitter affected their market performance. According to their findings, the relationship between Twitter sentiment and price movements was weak, and it remained relatively unchanged regardless of whether returns were measured relative to the market or if the market was calm or tumultuous. While the attitude expressed in financial news did seem to correlate with stock price changes, there was very little connection between non-financial news sources and price movements overall. Relative to the marketplace, the researchers also found that this association became stronger. In stable and unstable financial times, there are fewer connected businesses. The size of the correlation generally suggests that price movement drives sentiment, with the exception of the 2020 SARS-COV-2 pandemic, when the economy was experiencing a turbulent period.

Klaus and Koser (2021) used a new way to quantify the emotion of tweets, the Volfefe index, to study how Trump's tweets affected European financial markets. This index captured the volatility that Trump's tweets caused. Researchers in Europe discovered that while the Volfefe index increased trading volume, it significantly reduced profits and volatility for businesses and industries in the region. Additionally, the authors discovered that the Volfefe index's impact differed depending on the country, industry and company attributes, including size, leverage and export intensity. The authors drew the conclusion that investors should keep an eye on political leaders' social media activity and that Trump's tweets had significant spillover effects on European financial markets.

Metta et al. (2022) formulated a study to examine the effect of Elon Musk's tweets on stock prices. Research on Elon Musk's tweets included sentiment analysis. As of 9 March 2021, out of 630 tweets published by Elon Musk, 8.6 per cent were negative, 38.9 per cent were neutral, and the rest were positive. This suggests that tweets generally contain an emotion that can influence readers to react. This research also included an analysis of the content of seven equities based on eight selected tweets from Elon Musk. The researchers examined the equities' cumulative abnormal returns (CAR) as well as the tone of each tweet. Although three of the eight tweets showed no significant CAR associated with Elon Musk's actions, the other five had a notable effect on stock trading in the period immediately following the tweet and on the trading day it was released. Additionally, the analysis implied that Musk's tweets affected intra-day trading, since the market tends to adjust itself over a longer time frame due to supply and demand.

2.4. Research Focus

According to the aforementioned literature reviews and empirical investigations, financial information can be easily communicated and shared on social media, particularly Twitter, which in turn can affect market efficiency and the valuation of assets and businesses. Because they mirror and influence the market attitude and actions of traders and investors, sentiment and volume on Twitter can show and forecast financial returns and volatility. There is a longer horizon for correction, but the market can respond to the Twitter activity of powerful people like politicians and CEOs and move significantly, particularly when they announce or remark on policy or corporate choices. Nevertheless, the research does acknowledge the limitations and difficulties of relying on social media for financial information, particularly when it comes to the potential for manipulation and disinformation.

Chapter Three: Research Methodology

3.1. Introduction

The purpose of this chapter is to present the research methodology of the study. The chapter identifies the research hypothesis, the core design, the sources of data, the available methods for data analysis and choice of data analysis method. The researcher also details the core tools used for data analysis and the software used to conduct the assessment. The steps taken for data management and data filtering are detailed through this chapter.

3.2. Research Hypotheses

The core aim of the study is to evaluate the relationship between sentiment index and stock price change. The summary of past findings in Chapter 2 shows mixed evidence. For example, the study by Rahman and Patel (2016) contended that though there is a predictive power of social media sentiment on stock performance, the strength of the relationship is low and there are other more important factors. Rodriguez and Gomez (2018) and Thompson and Ellis (2019) also recognised that the relationship between social media sentiment and stock price movement is weak. On the other hand, other authors like Affuso and Lahtinen (2019), Chen and Dong (2023) and Kretinin et al. (2018) acknowledged a relationship between the two variables. Given that there are diverse outcomes, this research tests the following core research hypothesis:

H1: There is a statistically significant relationship between sentiment index and stock price change.

H2: There is a statistically significant relationship between sentiment index and stock price change within a rolling window period of one month, is rejected.

3.3. Research Design

This study adopts a quantitative research methodology where a comprehensive analysis of the relationship between sentiment and stock price is carried out. The researcher uses a time period of 1st January 2022 to 30th June 2022. This time period allows detailed examination of the impact of sentiment on stock price over a period of six months through focus on Apple.

3.4. Data Collection and Sources of Data

3.4.1. Twitter Data

Twitter data was identified from Tweepy. Tweepy is a Python library that provides an easy-to-use interface for interacting with the Twitter API. This open-source Python library simplified the researcher's interactions with the Twitter API. By enclosing the Twitter API's complexity and providing the model layer and other key practicalities, the API provides an interface. There are a number of classes and methods in Tweepy that make up the models and API endpoints of Twitter. It also transparently manages a plethora of technical details, such as encryption and decryption of information (Sarala et al., 2021). The process of accessing and manipulating Twitter data is simplified for users (Chowdhry and Niveditha, 2021). Tweepy provides information on Twitter data, user profile, trends and follower count. The researcher used the Tweepy platform to identify Tweets relating to Apple by extracting information on tweet language, tweet date and time, tweet content and information on the profile of the user. Appendix I presents the Python script that was used to identify and extract the tweet data.

3.4.2. Historical Stock Price Data

Other studies have used Yahoo Finance as the database to get information on stock prices. For example, Xu et al. (2014) recognised that Yahoo can be used as a tool as it not only provides historical data access but also allows the user to download the data and conduct additional analysis. It provides a significant amount of data free of charge, which provides advantages for individual investors and analysts requiring easy to access data. This database was used as it provides a user-friendly and easy interface allowing the researcher to collect the data. The researcher made use of Yahoo Finance to identify historical price data. Information is available on stock prices, including daily, weekly and monthly. Daily data provide open, high, low, close and adjusted close. The researcher selected stock price data from 1 January 2022 to 30 June 2022 to gather the relevant information.

3.5. Methods of Data Analysis

3.5.1. Sentiment Analysis

This section first evaluates the diverse methods used to conduct sentiment analysis across the different studies cited in Chapter Two. Only those studies which are most relevant to this research are used. In the study by Kretinin et al. (2018), the sentiment analysis was carried out using the Sentiment R package to convert the polarity score into more detailed outcomes. These include volume, sentiment classification and characterisation of keywords. In the study by Chen and Dong (2023), sentiment analysis was considered as an NLP technique. In this study, the authors used a learning approach for each stock based on existing lexicons for positive and negative sentiments. The authors made use of past studies which have identified these lexicons as part of R package "tidy text".

In the study by Dun Tan and Tas (2020), Bloomberg's social velocity data were considered to identify sentiments. The Bloomberg-integrated Twitter sentiment data used the raw message feed from StockTwits and Twitter. A proprietary natural language processing algorithm was then applied to classify every tweet. Such a classification method created a polarity score. The algorithm made use of positive, negative or neutral scores. Following this, the annotated data were used to create a sentiment index which was then fed into a machine learning model (support vector machine). This model provided company-level daily sentiment scores for both news and Twitter. In the study by Valle-Cruz et al. (2021), tweets were analysed using algorithmic computation using SenticNet. SenticNet provides an API which helped to evaluate the polarity of each word and transform this into a numerical value.

From the above analysis, it is clear that diverse tools (e.g. Sentiment R package) and databases (e.g. Bloomberg Sentiment database) have been used to conduct a sentiment analysis. In this research, due to lack of access to such tools—most of them are paid software and the researcher lacks expertise—an independent manual coding and analysis was carried out. The following section details the steps taken to conduct the manual coding process.

3.5.2. Impact of Sentiment Analysis on Stock Price

The methodology used to compare the sentiment index against financial performance was assessed. The review of literature showed the use of diverse methods to evaluate the relationship between Twitter sentiment and stock performance. For example, Chen and Dong (2023) used a decision-tree approach. In their research, they compared the decision-tree approach against a simple linear regression model, contending that the decision-tree is more effective in predicting future outcomes. Dun Tan and Tas (2020) evaluated the relationship between Twitter sentiment and stock trading volume and price using an abnormal turnover assessment. They used a linear regression analysis including firm size, cumulative market-adjusted returns and illiquidity measures over a specific period of time. Valle-Cruz et al. (2022) computed the correlation between financial indices and the polarity of posts published in Twitter using data-shifted correlation analysis. The authors conducted the analysis through programming using Python language.

3.6. Data Management and Analysis Procedures

3.6.1. Data Filtering for Tweets

The data obtained from Tweepy API were first evaluated using Microsoft Excel. The researcher used the filter function to isolate potential tweets that referred to the Apple Twitter handle (@Apple). The filtering process was intended to make sure that the dataset chosen was one that could provide accurate and relevant content for sentiment analysis. This sorting of tweets provided access to 946 tweets for analysis. The descriptives provided in the following table identify the follower count, favourites count and total number of tweets of these 946 tweets. According to Simon (2019), the follower count and total number of tweets made by an individual can be indicative of their degree of engagement on the platform and the number of followers that they can reach. Favourites count is an indicator of if the tweet is popular or well-liked, further acting as an indicator of sentiment. The following table provides some descriptives of these elements.

Table 1: Descriptives for Chosen Tweets for Initial Analysis

	Favourites Count	Followers Count	Total Tweets
Average	25521	29253	36221
Maximum	896564	5573625	1046066
Minimum	0	0	7
Standard Deviation	69378	286649	97837

3.6.2. Selection of Stock Price Data

The stock price analysis was carried out using historical stock price data. The dataset which was converted in MS Excel was evaluated to identify the end-of-day market valuation. According to Edwards et al. (2018) when evaluating stock price change, a consistent and widely recognised measure of stock performance for each trading day is the closing price of the stock. Therefore, the closing price of the stock was taken. The descriptive statistics of the stock data during the period is given below.

Table 2: Stock Data – Descriptive Statistics of Apple Stock Price

Average	159.98
Standard Deviation	13.29
Maximum	179.69
Minimum	130.059

3.6.3. Sentiment Index Calculation

A daily sentiment index was calculated using a weighted formula. According to Kumar and Jaiswal (2020), a manual process of coding tweets as positive, negative or neutral involves reading the tweet to carefully and subjectively assess overall sentiment that is identified within every tweet. The overall sentiment expressed is assigned a category (positive, negative or neutral). A tweet expressing a positive opinion (e.g. stock value, leadership, product quality, appreciation, sustainability) was rated as 1. If the tweet expressed a negative opinion (e.g. criticism, complaint, frustration with operations, lack of sustainability, poor leadership), it was rated as -1. If the tweet only stated a fact or provided information which did not have any clear sentiment (e.g. reference to Apple operations, retweet by others without relevance to product/brand), then it was rated as 0. Once this was calculated, a daily sentiment index was identified.

$$Daily\ Sentiment\ Index = \frac{\sum Sentiment\ value\ per\ day}{Total\ number\ of\ tweets\ per\ day}$$

This process was carried out using MS Excel pivot tables. Appendix II provides the VBA (Visual Basics for Applications) output for the same. The pivot tables were created by rows versus sentiment index. The aggregation function in the values area of the sentiment index was set to average. This approach provided the average sentiment index for each day, thereby facilitating an analysis of daily sentiment trends for Apple. This daily sentiment ranges between -1 and 1 on the basis of number of tweets per day. The following table provides the descriptives for the same.

Table 3: Descriptives of Sentiment Index

Average	0.082595061
Standard Deviation	0.296399292
Minimum	1
Maximum	-1

3.6.4. Calculating Stock Price Change

The next step of the analysis was to calculate the daily stock price change.

$$Percentage\ Stock\ Price\ Change = \frac{Close\ Price\ (today) - Close\ Price\ (Previous\ day)}{Close\ Price\ Previous\ Day}$$

The percentage change in daily stock price is most effective in understanding stock price volatility. It allows investors to compare price movement regardless of the starting point and is considered an important standardised approach to assessing strength and volatility within the portfolio against the market.

3.6.5. Data Management and Filtering

The next step is to compare the data available from the sentiment index against stock price change. Data management was essential as sentiment data was available for all dates while data on stock price change was only available for trading days. To address this discrepancy, the researcher filtered the dates for non-trading days. This included removing Saturday and Sunday data. Following this, the researcher removed sentiment data for US public holidays using the IF and V Lookup function as given in Appendix III. These steps ensured that there was a match between the data available for stock price change and ensured that the analysis was focused on trading days only.

3.6.6. Data Analysis

In this research, SPSS software was chosen for data analysis. According to Pallant (2020), the use of SPSS is ideal for novice researchers looking to perform complex statistical analyses without needing extensive programming knowledge. This tool was chosen as it can help conduct the regression analysis.

Regression Analysis

The first analysis carried out is a simple linear regression assessment to formally test the relationship between the sentiment index and stock returns. According to Montgomery et al. (2021), a simple linear regression tool is used to estimate the relationship between two quantitative variables. The goal of a simple linear regression analysis is to find the best-fitting straight line to explain the relationship between the variables. In this model, the daily stock returns served as the dependent variable while the sentiment index was the independent variable. The regression model is:

$$R_m = \alpha + \beta\, SI + \varepsilon$$

where Rm is stock return for day, SI is sentiment index, β is the coefficient of the impact of the sentiment index on stock returns, and ϵ is the error term.

Window Regression

This research makes use of a window regression methodology. This method analyses the relationship between variables by using a fixed window of data. This approach is used to characterise changes in economic relationships over a period of time. According to Ziwot et al. (2003), a window regression is effective in conducting analysis during a specific time period. The regression analysis helps capture temporal variations in data analysis. In sentiment analysis, a rolling window can help determine if there is a specific time period during which sentiment may impact stock price. Valle-Cruz et al. (2021) identified that there is a 5–15-day window where there is an impact on stock prices of a specific announcement or news. In this research, the researcher used a one-month window (one working week, excluding trading holidays) for assessment. The researcher conducted a monthly window, repeating the regression analysis for the new subset using case selection methodology.

Chapter Four: Findings and Discussion

4.1. Introduction

The purpose of this chapter is to present the findings and discussion of the study. The chapter presents the study results to test the different hypotheses proposed in Chapter Three.

4.2. Test for Normality

The researcher first conducted the test for normality using the Shapiro-Wilk test for the independent and dependent variables. With a significance value of more than 0.05, the test for normality is accepted. Therefore, the researcher can continue to make use of parametric tests.

4.3. Descriptive Analysis: Tweets – Sentiment Analysis

An independent manual coding of the tweets from Apple shows that most of the tweets are neutral. There are more positive tweets (n=150) than negative tweets (n=51). The following figure shows the distribution of sentiment across the tweets.

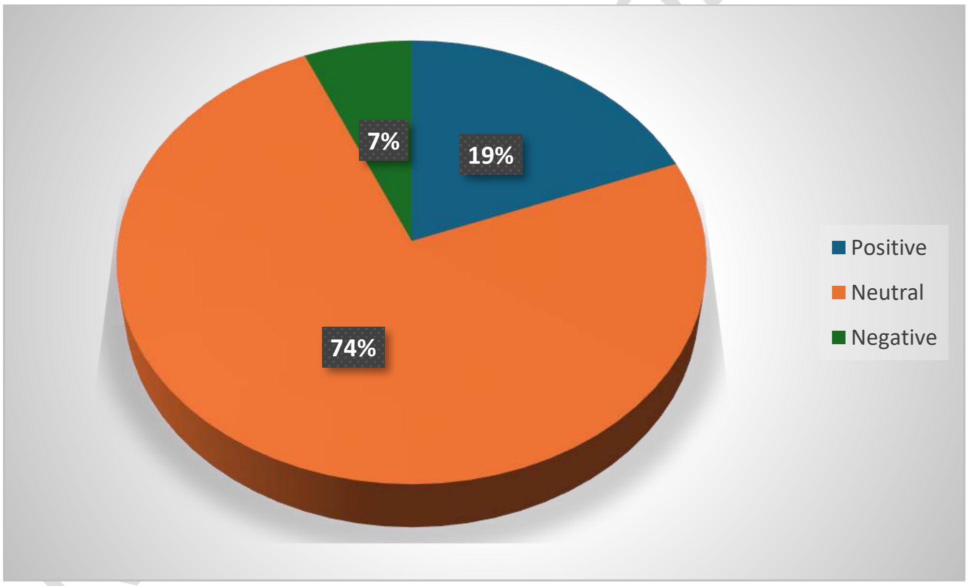

Figure 1: Tweet Sentiment Percentages

The researcher manually coded these tweets to identify core parameters contributing to positive and negative sentiment. The following table characterises these overall themes.

Table 4: Positive and Negative Sentiment of Tweets

Sentiment	Themes	Description
Negative	Loss of revenue	Tweets that discuss reduced revenue or financial losses for the company
	No innovation	Complaints about lack of new or groundbreaking products or ideas
	Lack of updates, unnecessary spending	Mentions of unnecessary spending, lack of updates of existing products
	Tracking	Concerns or dissatisfaction regarding tracking user behaviour
	Problems	Tweets highlighting general issues with the company's products or services
	Low satisfaction	Dissatisfaction or frustration with products or customer service
	Exorbitant	Complaints about high prices of products or services
	Stock buyback	Negative opinions on the company buying back its stock instead of investing
	Poor leadership	Lack of leadership support.
Positive	Profit	Tweets mentioning company profitability or financial success
	Revenue per employee	Appreciation for high revenue generated per employee
	Masterpiece	Praise for specific products or the company's innovation
	Blockbuster	Celebrations of successful product launches or business ventures
	Record revenue / sales	Tweets that focus on record-breaking revenue or sales figures
	Blow out	Extreme positivity about a successful financial quarter or product release
	Astonishing growth	Tweets highlighting significant growth in various aspects of the company
	Appreciation	General admiration and respect for the company's products or achievements
	Innovation growth	Positive remarks regarding the company's continued innovation and expansion

These themes were also evaluated through content analysis as identified in Tables 4 and 5. Positive tweet analysis shows that the most common positive aspects highlighted are Apple's revenue generation (n=48) and profitability (n=35). Reference is also made to different Apple products and support given by personnel. The importance of growing innovation and support given to identify new options and tools is also evident (n=12). On the other hand, when evaluating the nature of negative tweets, poor leadership (n=8), focus on stock buyback (n=3), stagnancy and loss of revenue (n=10) are evident.

Table 5: Positive Tweets – Content Analysis

	Content analysis of positive tweets
Profit	35
Revenue generation	48
Leadership and strategy	8
Masterpiece products	12
Blockbuster hit	5
Record revenue / Sales	2
Astonishing growth	29
Appreciation for product/sales/support	27
Innovation growth	12

Table 6: Negative tweets – content analysis

	Content analysis of negative tweets
Loss of revenue	10
No innovation	6
Product lacks update	1
Tracking	1
Problems with product/service	5
Low satisfaction	6
Exorbitant	4
Stock buyback	3
Leadership	8

These views can be compared to those in literature. There are studies that offer insights into Twitter sentiments. For example, Bollen et al. (2011) analysed the textual content of daily Twitter feeds using two mood tracking tools, finding more positive than negative tweets. Nisar et al. (2018), in their analysis of social media and stock market behaviour by assessing political campaign-related tweets, ascertained that negative tweets had more impact on outcomes. Pagol et al. (2016), in their assessment of Microsoft news on Twitter regarding company stock and opinions on products and services, concluded that while many tweets may be neutral, those which are positive or negative have the most impact on stock market outcomes.

4.4. Regression Analysis

The researcher first conducted a simple regression analysis with the dependent (stock price percentage change) and independent (sentiment index) variables. The purpose of the regression analysis was to test the following regression equation:

$$R_m = \alpha + \beta\, SI + \varepsilon$$

where Rm is stock return for day, SI is sentiment index, β is the coefficient of impact of sentiment index on stock returns, and ϵ is the error term.

From the following table, it is observed that an R^2 value of 0.35 is evident, indicating moderate goodness of fit for the regression equation. The ANOVA table is intended to identify the F value. The coefficients table is intended to provide overall outcomes of the regression analysis. From the table, it is seen that there is a significant positive relationship between the sentiment index and stock value change (t=2.563, p=0.041). With a beta value of 0.014, the research shows that the sentiment index has a weak impact on stock price change. For every one unit change (increase) in the sentiment index, there is only a corresponding 0.014 unit change in the asset price.

Table 7: Simple Linear Regression

Model Summary				
Model	R	R^2	Adjusted R^2	Std. error of the estimate
1	.187[a]	.350	.271	.02245
a. Predictors: (Constant), sentiment index				

Model		Unstandardised coefficients		Standardised coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.003	.002		1.520	.131
	Sentiment index	.014	.007	.187	2.563	.041
a. Dependent variable: stock value change						

These views can be compared to those in literature. Chen et al. (2014) conducted a study that demonstrated that investment-oriented social media platforms are cost-effective instruments for stock market research and the dissemination of company-specific information. Chen et al. (2014) conducted a study that demonstrated that chief financial officers and chief executive officers who participate in social media platforms such as LinkedIn, Twitter and Facebook can improve the dissemination of news about their companies within financial markets. This enables senior executives to further their personal objectives. In order to evaluate the intensity of emotions, Ren et al. (2021) conducted research on the prevalence of emotionally charged vocabulary in online evaluations. The results of their research suggest that the emotional intensity of online evaluations has a substantial impact on product sales. This perspective suggests that an acute emotional attachment to a subject may have a substantial impact on attention and may motivate individuals to seek out more informed sources of information. This plainly illustrates the correlation between consumer behaviour, information-seeking behaviours and online sentiment. A potential explanation is that the growing polarisation of opinions on social media regarding a controversial issue serves to reinforce the correlation between the consumption of online news and traditional news. The attention that emotions in social media postings attract grows, along with the intensity of emotions, resulting in a more robust correlation between social media engagement and visits to news websites. It is therefore reasonable to infer that social media and online attitude influence both consumer and investment behaviour, affecting stock markets.

Taking stock index returns with subsequent reversals as an example, we can see that market-level news sentiment predicts them (Tetlock, 2007; Garcia, 2013). On the other hand, through the dissemination of value-relevant information, we discover that firm-level sentiment on Twitter impacts stock returns. There are two reasons for the contradictory results. Firstly, the data landscapes surrounding stock indices and specific equities are distinct. In most cases, stock index values are more efficient than stock prices of individual firms. Media content pertaining to firms may have a longer return predictive ability since firm-level information takes longer to trickle down into stock prices than market-level information. Secondly, the development of a reliable online infrastructure has made social media platforms crucial for the dissemination of information by both private citizens and public agencies. Social media platforms like Twitter enable investors to share their thoughts on equities and financial markets in real time, unlike traditional media. So, news from social media is more likely to be up to date and valuable than news from more traditional sources.

4.5. Window Regression Analysis

The researcher conducted a windows regression analysis assuming a specific time period. The regression analysis carried out is expressed below. From Table 6 below, it is seen that even when a window perspective is adopted, there are some periods where there is evidence of a significant relationship between the variables, while in one time period there is a lack of evidence of a relationship between sentiment index and stock price change. Therefore, the impact is not consistent and may vary across time periods. From this analysis, hypothesis H2 is rejected.

i.e.,

H2: There is a statistically significant relationship between sentiment index and stock price change within a rolling window period of one month, is rejected.

Table 8: Windows Regression Analysis

Window Cycle	**R^2**	**Sentiment index T-value**	**Sentiment index p-value**
1	0.36	3.14	$P<0.05$
2	0.009	0.38	$P>0.05$
3	0.006	0.35	$P>0.05$
4	0.24	0.64	$P>0.05$
5	0.05	0.97	$P>0.05$
6	0.05	1.027	$P>0.05$

There are studies that have evaluated the impact of rolling windows regression for stock price prediction. For example, Henrique et al. (2018) evaluated the use of support vector regression with rolling windows to predict stock prices. In their study, they included sentiment analysis as a variable. The authors identified that considering the day of week effect and rolling windows is essential to better predict the relationship between sentiment analysis and stock price change. Ngyuen et al. (2015) evaluated the effectiveness of sentiment analysis and stock price prediction by evaluating 18 stocks. They found that by considering a window time period, it is possible to better predict time periods where the stock price is influenced by sentiment. Xu et al. (2021), in their dynamic cross-correlation analysis between online sentiment and stock market performance, concluded that the cross-correlation relationship between financial market returns and online sentiments may relate to some time periods more than others. A similar approach is evident in the current study. According to Ji et al. (2023), when using a fixed time period, it is possible to assess the stability of a proposed model and its forecast accuracy. The weak relationship between sentiment analysis and stock market performance is reflected in the current study.

4.6. Policy and Business Implications

The purpose of this dissertation was to evaluate the relationship that exists between tweets or Twitter posts and the influence on stock price. As argued in Chapters One and Two, through social media engagement it is possible to identify the impact of sentiment change and its potential influence on stock price, and thereby the financial stability of the firm. This research sought to discuss this relationship through a focus on a single stock, Apple. In their study, Sun and Zheng (2022) proposed the sentiment efficient markets hypothesis, where they argue that investor sentiment has a direct information on asset price while information has an indirect effect influenced by sentiments. Some important business and policy implications are discussed in this study.

4.6.1. Business Implications

There is a definite relationship between social media sentiment and the stock price or financial stability of the firm. Therefore, it is important for Apple to keep track of information that is shared on social media, especially after specific events (e.g. announcements on new products, earnings announcements). Apple needs to monitor this sentiment and perhaps respond to some of the direct comments that could affect the valence of future tweets or social media posts. At the business level, the importance of social media sentiment should be discussed. While there is a relationship between tweets and change in stock price, this relationship is definitely weak. This is indicative of the idea that corporations like Apple cannot rely only on social media sentiments, focusing on their direct Twitter handles. There are many tweets which may relate to Apple but do not tag the brand. It is important for Apple to consider social media sentiments while also considering other sources of information that may influence stock price change. Apple and other businesses need to complement their sentiment analysis of Twitter with other indicators while making stock-related decisions.

Another important business implication is investor-level assessment of sentiment indices as tools for decision-making. As part of investor relationship building, the tweets from analyst organisations and individual financial experts needs to be considered by firms. Market factors like earnings reports, global events, industry trends and investor response need to be constantly monitored.

4.6.2. Policy Implications

The first policy implication is the guideline on sentiment analysis. Though there is some evidence of the SEC focusing on announcements on social media. clear guidelines on how sentiment analysis can be used is missing. For example, Bloomberg Terminal has a sentiment assessment tool used to highlight the current trend on social media about a specific stock (Garcia, 2022). In this context, it is important that specific regulatory guidelines are made available on sentiment analysis and its accessibility. The second policy level indicator is the question of data use. There is evidence of both corporations and financial analysts making use of social media data to assess sentiment. It is essential to evaluate if these actions are in line with broader transparency and data use guidelines. Policymakers need to be aware of how data can used safely in order to reduce concerns related to privacy and data use. They need to push for solutions on how to use these data better to avoid an over-reliance on one type of analysis.

Chapter Five: Conclusion

5.1. Revisiting Research Question

The primary research question of this study was:

What impact does public sentiment on Twitter (measured through sentiment analysis) have on stock price performance and the financial stability of Apple Inc?

To answer this question, there were three key objectives.

The first objective was to do a sentiment analysis of the target corporation's tweets to establish a sentiment index by categorising tweets as positive, negative or neutral. An autonomous manual analysis of the tweets from Apple indicates that the majority of the tweets are neutral. The quantity of positive tweets exceeds that of negative tweets. Negative tweets relate to revenue loss, absence of innovation, insufficient updates, excessive expenditure, dissatisfaction, inflated pricing, inadequate leadership, and stock buybacks. Favourable tweets pertain to profit, revenue per employee, quality product, record revenue/sales, innovation and expansion.

The second objective was to analyse the influence of this sentiment index on the company's stock price performance. The researcher initially performed a straightforward regression analysis using the dependent variable (stock price percentage change) and the independent variable (sentiment index). The research indicates that the sentiment index exerts a negligible influence on stock price fluctuations, as evidenced by a beta value of 0.014. For each one-increase in the sentiment index, there is a corresponding shift of only 0.014 units in the asset price. Even when a window view is utilised, certain intervals exhibit a substantial link between the variables, yet others, there is an absence of evidence linking the sentiment index to stock price fluctuations.

The final objective was to provide recommendations, which are discussed below.

5.2. Recommendations

The first broad theoretical implication of this study is the need for more focused research on emotional finance. According to Taffler (2018), it is important for researchers to address emotional finance as a subsection of behavioural finance. The author contends that sentiment is not just driven by irrational bias, explaining that there can be diverse positive and negative factors. In this study, while there is a weak relationship between the sentiment index and stock returns, it is important to recognise other factors that may act in addition to stock-specific sentiments. For example, some authors indicate that the sentiment effect of information gathered from Twitter can be a result of diverse information including external events, economic indicators and geopolitical risks (e.g. Katsafados et al., 2023) Additionally, as Bollen et al. (2011) contend, it is important to address other factors that influence the sentiment impact of traditional news media along with the social media effect. This research acknowledges the need for more research on emotional behaviour finance.

Another important research recommendation is to better understand the role of the valence of sentiment impact. For example, Sul et al. (2014) contend that there is greater impact of negative tweets on stock price outcomes. In our research, the observations show more positive than negative tweets. It is recommended that more research on potential asymmetric influence is carried out, wherein it is possible that bad news might cause sharper declines than good news. Therefore, it is important to consider the valence of social media. According to Sul et al. (2011), there is established evidence of positive emotions having a strong likelihood of causing action, while the impact of negative information needs to be better understood. Similarly, the authors argue that neutrality or calmness of emotion in tweets can also predict future performance. Given that most of the tweets in this study were considered to be neutral, it is important to evaluate the specific role of calmness and its valence along with other emotions like emotional arousal in predicting stock market returns.

The third important factor that should be discussed is the impact of user profile. According to Sul et al. (2014), Twitter users who have more followers have a greater impact on same day stock returns than users who have fewer followers. This dissertation concludes that understanding the role of analysts is important in sharing information on social media platforms. A key implication of this study is that the economic significance of the nature of the user and their characteristics on stock market research should be better evaluated and assessed.

5.3. Limitations of Research and Future Research

This study has some important limitations that need to be addressed. The first limitation of the study is the choice of a single organisation and a single six-month window (January to June 2022). The targeting of a single organisation could be indicative of challenges when it comes to generalising the study outcomes and determining the relationship between stock price index and sentiment change. The researcher also recognises that there can be potential challenges linked to the choice of a specific time period without comparing against other organisations or broader outcomes.

The second limitation of the study is that there is exclusive use of linear regression analysis to evaluate the relationship between investor sentiment and stock prices. There are other advanced tools, like Granger causality, machine learning and time-series analysis, that can be used to arrive at relevant study outcomes.

The third limitation of the study is that the coding of sentiment data was carried out manually. This is indicative of potential biases, which can in turn limit scalability. It is important that sentiment analysis tools like SenticNet and others that leverage natural language processing are included in future research.

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Appendix I

Tweepy Code for Data Extraction

```
import tweepy

import pandas as pd

from datetime import datetime

# Example Twitter API credentials (replace these with your actual credentials)

API_KEY = 'XvT4yaQJjvLg5bU8PlmAe9oWZ'

API_SECRET_KEY = 'eP7hjkGr5ytPq7sR4aVwNtB6lJkKxQmZnOh5yUx'

ACCESS_TOKEN = '129837465-LpOpVkTiWu8z7AfRfHaGnLmPxUiN0Op3kLmR1zX'

ACCESS_TOKEN_SECRET = 'aBtP8vQpL5eWt7dXyJlXvZrFn6hKq5nPq7vZtWmQ'

# Authenticate to Twitter

auth = tweepy.OAuthHandler(API_KEY, API_SECRET_KEY)

auth.set_access_token(ACCESS_TOKEN, ACCESS_TOKEN_SECRET)

api = tweepy.API(auth, wait_on_rate_limit=True)

# Define the search query and date range

query = 'apple'

start_date = '2022-01-01'

end_date = '2022-06-30'

# Create a list to store the tweets

tweets_data = []

# Fetch tweets

for tweet in tweepy.Cursor(api.search_tweets, q=query, lang='en', since=start_date, until=end_date,
tweet_mode='extended').items():

    tweets_data.append({

        'date': tweet.created_at,

        'text': tweet.full_text

    })

# Convert to a DataFrame

tweets_df = pd.DataFrame(tweets_data)

# Save to a CSV file

tweets_df.to_csv('apple_tweets.csv', index=False)


print(f'Successfully fetched {len(tweets_df)} tweets and saved to apple_tweets.csv')
```

Appendix II

Calculation of Sentiment Index using MS Excel - Pivot Table

```
Sub CreateSentimentPivotTable()

    ' Define variables
    Dim ws As Worksheet
    Dim pivotWs As Worksheet
    Dim dataRange As Range
    Dim pivotTable As PivotTable
    Dim pivotCache As PivotCache
    Dim lastRow As Long

    ' Set worksheet and range for data
    Set ws = ThisWorkbook.Sheets("Sentiment data by date") ' Adjusted sheet name
    lastRow = ws.Cells(ws.Rows.Count, "A").End(xlUp).Row ' Find last row with data
    Set dataRange = ws.Range("A1:B" & lastRow) ' Adjust range based on actual data

    ' Add a new sheet for the pivot table
    Set pivotWs = ThisWorkbook.Sheets.Add
    pivotWs.Name = "SentimentPivot"

    ' Create pivot cache
    Set pivotCache = ThisWorkbook.PivotCaches.Create( _
            SourceType:=xlDatabase, _
            SourceData:=dataRange)

    ' Create the pivot table
    Set pivotTable = pivotCache.CreatePivotTable( _
            TableDestination:=pivotWs.Range("A1"), _
            TableName:="SentimentPivotTable")

    ' Configure pivot table fields
    With pivotTable
```

```
    .PivotFields("Tweet_DateTime").Orientation = xlRowField ' Using 'Tweet_DateTime' as date
    .PivotFields("Sentiment").Orientation = xlDataField ' Using 'Sentiment'
    .PivotFields("Sentiment").Function = xlAverage ' Set to Average
  End With

  ' Filter data to include only the desired date range
  With pivotTable.PivotFields("Tweet_DateTime")
    .ClearAllFilters
    .PivotFilters.Add Type:=xlDateBetween, Value1:="2022-01-01", Value2:="2022-06-30"
  End With

  ' Optional: Autofit columns for readability
  pivotWs.Columns.AutoFit

End Sub
```

Appendix III

Data Exclusion for trading days

```
=FILTER(
  'Categorisation by date'!A:C,
  (('Categorisation by date'!B:B<>"Saturday") *
   ('Categorisation by date'!B:B<>"Sunday")) *
   ISERROR(MATCH('Categorisation by date'!A:A, 'Holiday list'!A:A, 0))
)
```