JGB 1740

Investigating the Relationship between CEO Twitter Activity and Stock Market Performance

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Abstract

For the past decade, social media has become one of the essential data sources for businesses and investors. Businesses and investors can benefit from analyzing social media data in the context of the financial market. Social media is used to help predict sales and analyze trends and a strategy for improving the company's marketing and advertising. Tweets of stock market traders and investors have a significant impact on stock market returns as well. Given the growing importance of social media in business, this paper aimed to determine the relationship between CEO tweeting activity and stock market outcomes. The researchers used datasets that consisted of tweets made by the CEOs of the top five companies in the S&P 500. The company's CEO's tweets from 2016 to 2020 were scraped using Twint. The dataset for the stock prices was taken from Yahoo Finance using the DataReader package. The collected data were preprocessed, and the final dataset consists of the sentiment scores of the CEOs' tweets and adjusted closing stock prices. Valence Aware Dictionary and Sentiment Reasoner (VADER), a *lexicon sentiment analysis tool, was used to determine the sentiment scores of the tweets. Results showed that the impact of the sentiments of Twitter posts on the stock prices varied among the different CEOs. The results also show that some CEOs with Twitter activities had a more substantial influence on their company's stock prices, though on a limited scale. Moreover, Linear Discriminant Analysis was used to determine the relationship between the topics of the CEO tweets and changes in the stock market by analyzing the topics of the tweets over time. The CEO's Twitter activity positively impacts the stock market prices, though not significantly.*

Keywords: *Sentiment Analysis, Stock Market, Twitter, Tweet, Social Media Activity*

Introduction

One of the major significant sources over the past ten years has been social media. There are 237.8 million using Twitter day after day as of the second quarter of 2022, and at least 500 million tweets were sent daily (Ruby, 2022). Dolega, L., Rowe, F., & Branagan, E. (2021) stated that social media had become an important digital marketing tactic to promote business products and increase revenues. A study by Duz Tan, S., & Tas, O. (2020) stated that investors are more active on the Twitter platform, and have been increasing for years. Another study by Bordino et al. (2018) compared traditional survey-based sentiment indicators with Twitter data to evaluate sentiment analysis's efficacy. The results showed that social media data, particularly Twitter, could offer insightful information about market sentiment and more accurately forecast financial market trends than conventional survey-based indicators.

Moreover, a company's marketing and advertising can be improved by utilizing a social media influencer who uses its products and promotes its brands (Omand et al., 2012). Mao et al. (2012) stated that Twitter is intriguing and well-liked in the research field, given that it is among the most widely utilized social media platforms and operates concurrently. Everyone may receive news, thoughts, and feelings on Twitter with a single mouse click in less than one second, making Twitter an essential data source for extensive data analysis. Furthermore, the study shows that Twitter use has a sizable impact on stock market returns. However, there should be a demand for research on how Twitter use by CEOs affects stock market activity (Mao et al., 2012), just like how CEOs' comments during television interviews impact the stock market. (Meschke, 2004). The relation between CEO tweets and stock market value was shown when the Tesla CEO, Elon Musk, posted a misleading tweet about the secured funding of Tesla Private. This resulted in SEC filing a claim against Musk for spreading untrue information that significantly impacted the stock price. This resulted in a considerable 14% drop in the stock price (Kelleher, 2018). There is vast uncertainty in how the stock market works and is affected by many things, including social media posts. So, making predictions about the stock market is essential to finance and business (Attigeri et al., 2015). Predicting the stock market is an important and challenging area of research that has been going on for many years (Attigeri et al., 2015).

Sentiment Analysis (SA) is a field of study that integrates NLP, machine learning, data mining, and information retrieval (Xu G et al., 2019). In Sentiment Analysis, Individual views and expressions are categorized as positive, negative, or neutral. Sentiment analysis is best described as extracting data based on user sentiment (Krishnamoorthy, S. 2018). As part of Sentiment Analysis, opinion mining is gathering and analyzing people's opinions, feelings, attitudes, perceptions, etc., toward various subjects, products, and services (Birjali, M et al., 2021). A recent study by Zhang, L., Wang, S., & Liu, B. (2018) stated that sentiment analysis has also become very popular recently, producing state-of-the-art results in many application domains. Sentiment analysis helps to understand the effect of social media posts and comments on the stock market. This research aims to investigate whether there is a relationship between a company's CEO's Twitter activity and stock market price. Specifically, the research will explore whether the sentiments of CEOs via tweets can determine how the stock market is likely to react and whether these sentiments can lead to more accurate stock market predictions.

Specifically, the researchers look to answer the following inquiries:

1. What is the relationship of CEO tweets to their company's stock prices?
2. How do the different CEO tweets affect the stock market price?
3. Can the sentiment of CEO tweets be used to classify their company’s stock price?

The study has the potential to impact the global business landscape. As Duz Tan, S., & Tas, O. (2020) highlighted, throughout recent years, platforms like Twitter and message boards have gained significance in decision-making processes. Investors have begun basing their trading decisions on the information derived from these social media tools. Twitter's extensive reach and real-time nature make it a vital channel for CEOs to express their thoughts and opinions and influence market behavior. For instance, the notable case of Elon Musk's tweet impacting Tesla's stock price (Kelleher, 2018) exemplifies the significant consequences of CEO Twitter activity on stock market performance. By delving into this instance, the research sheds light on how CEO sentiments expressed through tweets can shape stock market reactions and potentially lead to more accurate predictions. Understanding and harnessing this dynamic may have far-reaching implications for global businesses.

Review of Related Literature

The paper by Pagolu et al. (2016), "Sentiment analysis of Twitter data for predicting stock market movements," explores the relationship between Twitter sentiments and the stock market change by getting the tweets of different companies and performing sentiment analysis on them using various natural language processing. The result of the paper showed that sentiment analysis of Twitter might be utilized to forecast stock market movements and demonstrated that machine learning algorithms had an accuracy of about 70% in predicting the course of stock market movements. The study also discovered that the type of stock and the time interval (a day, a week, or a month) impacted the prediction's accuracy. However, the author acknowledges the study's limitations, such as the bias where most of the Twitter data they used are mostly the general population and only some who trade in stocks, and further recommends improving the accuracy of the approach.

Another literature entitled "Blockbuster: Predicting movie success using social network community sentiment analysis," by Ranjan and Sood (2019) provides an extensive study regarding the effects of social media in predicting the success of blockbuster movies according to the analyzed sentiments of acquired public tweets for movie-related Twitter hashtags. Analyzing the emotions expressed on Twitter can create models that accurately predict if blockbuster movies will succeed or fail. Movie distributors can utilize this data to modify their marketing tactics and influence the public's perception, which will increase sales. The study discovered a strong relationship between the sentiments of social network communities—specifically, the general sentiment of tweets and Facebook posts about a particular movie—and the film's box office performance. The results indicated that machine learning algorithms had an accuracy of about 80% in forecasting the box office success of the films.

A similar literature by Sattarov et al. (2020) titled "Forecasting Bitcoin Price Fluctuation by Twitter sentiment analysis" investigates the price fluctuation of Bitcoin. It examines Bitcoin-related tweets with financial data using a sentiment analyzer. This study used the Valence Aware

Dictionary and Sentiment Reasoner (VADER) for sentiment analysis on the tweets, which can result in a polarity score of 1 or -1 where -1 is negative, 0 is neutral, and one is positive. Results showed a strong correlation between the fluctuation of price and sentiments. However, the paper may be improved by having a Bitcoin sentiment lexicon to improve the sentiment analysis on Bitcoin fluctuation.

Research by Gurrib et al. (2021) titled “Bitcoin price forecasting: Linear discriminant analysis with sentiment evaluation.” showed that using a linear discriminant analysis-based classifier on current bitcoin price information and the sentiments of Twitter headline news regarding bitcoin showed that it could accurately classify the direction of the price of bitcoin the next day. According to the study, LDA with sentiment analysis had a 74.7% accuracy rate in predicting changes in bitcoin prices. The study also indicated that the sentiment of the tweets significantly influenced how much the price of bitcoin changed, with positive sentiment being linked to an increase and negative sentiment to a decrease.

A study using linear discriminant analysis was also used to classify if a company will experience financial distress as an early warning sign for a company. This study was conducted by Santoso, N & Wibowo, W. (2018) titled “Financial distress prediction using linear discriminant analysis and support vector machine” as a way for companies to evaluate their status of the company in terms of their financial situation, especially if their status can lead to bankruptcy. Based on the study, both LDA and SVM were highly accurate at predicting financial distress. Liquidity ratio, debt-to-equity ratio, and asset turnover ratio were among the financial ratios that the study found to be highly reliable indicators of financial distress.

About a company's performance a study by Wang, S. & Chen, X. (2020) titled "Recognizing CEO personality and its impact on business performance: Mining linguistic cues from social media" studied the impact of a CEO's personality on the performance of their business by examining their social media posts and based on the study CEOs with higher levels of agreeableness and conscientiousness typically had better business performance, while CEOs with higher levels of neuroticism typically had worse performance.

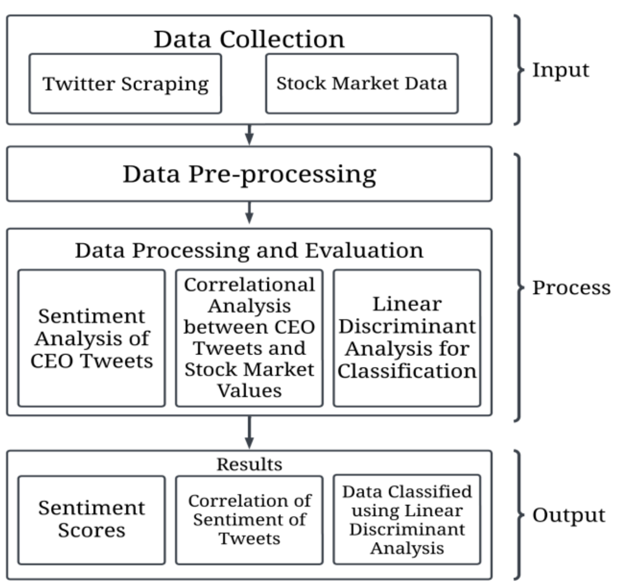
Framework of the Study

This paper used the Input-Process-Output framework, as shown in Figure 1. The Input phase is the collection of data that scraped CEO tweets and the stock market data. The Process phase is the phase to pre-process the data and evaluate the data using various techniques, such as sentiment analysis, correlation analysis, and LDA classification.

Finally, the results will show the sentiment score of CEO tweets, the correlation of sentiment of tweets, and the accuracy of data classification using LDA analysis. The framework is further discussed in the methodology section of the paper.

Figure 1

IPO Model



Methodology

In line with the objectives of this project, the appropriate design for conducting this study is using the quantitative approach because this study aims to get the correlation between the sentiments of the CEOs to the stock price of their companies and be able to classify if the company's stock price increases or decreases using the sentiment scores of CEO tweets.

Dataset Collection

The dataset consists of tweets made by the CEOs of the top five companies in the S&P 500, which include Apple (Tim Cook), Amazon (Jeff Bezos), Google (Sundar Pichai), Microsoft (Satya Nadella), and Tesla (Elon Musk). The tweets were scraped using a Twitter intelligence tool called Twint. The tweets taken were from the company's CEOs from the start of 2016 until the end of 2020. The dataset for the stock prices was taken from Yahoo Finance using the DataReader package. The final dataset consists of a combination of the stock prices, precisely the adjusted closing price, the sentiment scores of the CEOs' tweets, and the following dates for the stock price and the sentiments.

Sentiment Analysis

Valence Aware Dictionary and Sentiment Reasoner (VADER), a tool used to acquire sentiments expressed in social media using lexicon sentiment analysis, are used to determine the sentiment of each tweet in the dataset. Sentiments generated can be categorized into negative, positive, and neutral. Each category is assigned a number ranging from zero to one, indicating their sentiment score in a category. Zero is the lowest, which is negative, and one is the highest, which means the sentiment is positive. Additionally, Vader can generate a compound score ranging from a positive to a negative one, the positive one being the most positive sentiment and the negative one representing the most negative.

Correlation of Sentiments to Stock Price

The researchers aim to determine the relationship between sentiments and stock prices by using the Pearson correlation coefficient to the sentiment scores provided by VADER and the adjusted closing price of the chosen stocks. The Pearson correlation coefficient quantifies the statistical degree of relationship between variables. Positive values indicate a positive correlation and negative values signify a negative correlation.

Table 1 describes the scale for interpreting correlation coefficients (r) and their corresponding indications. A correlation coefficient measures the strength and direction of the linear relationship between two variables.

Table 1

Scale of Pearson's Correlation Coefficient Interpretation

The scale of the correlation coefficient (Absolute value)	Indication
0.01 - 0.19	Very Low (Positive/Negative) Correlation
0.2 - 0.39	Low (Positive/Negative) Correlation
0.4 - 0.59	Moderate (Positive/Negative) Correlation
0.6 - 0.79	High (Positive/Negative) Correlation
0.8 - 1.0	Very High (Positive/Negative) Correlation

Note. Adapted from *"Statistics for business and economics"* Newbold, P.,2013, Pearson.

Linear Discriminant Analysis

The dataset was pre-labeled into two groups: one group where the adjusted closing price increased compared to the opening price and the other where it decreased based on the stock price of the next date.

LDA was also used to classify our data points into two classification groups: the first classification group describes if the stock price will decrease, and the second classification group describes if the stock price will increase.

Normalization is used to standardize the scale of each feature. A min-max feature scaling approach is employed, which rescales the features to a range of 0 to 1. This is achieved by using the formula X_scaled = (X - X_min) / (X_max - X_min), where X represents the original value of the variable, X_min is the minimum value of the variable in the dataset, and X_max is the maximum value of the variable in the dataset. By bringing all features to a similar scale, the accuracy of the LDA model is improved as it prevents any single feature from exerting excessive influence over others. Additionally, normalization aids in mitigating overfitting by reducing the impact of noise or outliers in the dataset on the LDA model.

Table 2 presents an interpretation of specific score-level intervals using Linear Discriminant Analysis involving its accuracy, Precision, Recall, and F1-score.

Table 2

Interpretation of Accuracy, Precision, Recall, F1-score Score Levels

Score Level	Interpretation (Accuracy/Precision/Recall/F1-score)
0-0.39	Probable Reverse Relation
0.40-0.59	Random Relation/Unrelated
0.60-0.69	Low Score
0.70-0.79	Moderate Score
0.80-0.89	High score
0.90-1.00	Very High Score

Note. Adapted from "The elements of statistical learning: data mining, inference, and prediction" (Vol. 2, pp. 1-758), Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H., 2009, Springer.

Discussion of Results

This research investigates the relationship between CEO Twitter activity and stock market performance by determining the relationship between sentiments and stock prices using the Pearson correlation score and LDA implementation to classify the direction of stock prices for certain companies.

Correlation between stock price and CEO sentiments from tweets

Table 3 presents the relationship between stock prices and CEO sentiments from tweets using the Pearson Correlation Coefficient.

Table 3

Pearson Correlation Scores of the Sentiments from the CEO Tweets to the Stock Price

CEO	Correlation Score
Tim Cook (Apple)	0.13
Jeff Bezos (Amazon)	0.28
Sundar Pichai (Google)	0.08
Satya Nadella (Microsoft)	0.02
Elon Musk (Tesla)	0.02
All CEOs	0.45

Among the individual CEOs, Jeff Bezos has the highest correlation score of 0.28, which suggests a positive correlation between his tweets and the stock market prices of Amazon. However, the correlation score is still slightly low, indicating that their tweets affect the stock prices but are not drastic enough to change the stock market price.

Tim Cook has a correlation score of 0.13, which is also a low positive correlation score. Sundar Pichai has one of the lowest correlation scores of 0.08, suggesting an even lower correlation between his tweets and Google's stock market prices.

Satya Nadella and Elon Musk have the lowest correlation scores of 0.02, indicating an even lower correlation between their tweets and the stock market prices of Microsoft and Tesla, respectively.

Despite the low correlation scores of each CEO, their tweets exhibit a positive correlation with the stock prices, indicating that their tweets have the potential to impact the stock market prices. A study by Harrison, J et al. (2020) observed that a CEO's public perception could affect the stock market based on their verbal and behavioral cues. This can also translate to the tweets made by the CEOs, which is supported by the study of Andrea S et al. (2020), which suggests that CEO tweets can help shape investor perceptions of a particular stock investment, albeit not to a significant extent. The overall correlation score for all CEOs is 0.45, indicating a moderate positive correlation based on the scale of correlation coefficients in Table 1. This suggests that there is a relationship between the tweets of CEOs and the stock market prices of their respective companies.

Bollen et al. (2020) study focuses on the predictability of stock market movements by analyzing Twitter sentiment. They found a connection between sentiment on Twitter and stock market fluctuations. The result of their study was that there is a connection between the sentiment expressed on Twitter and subsequent stock market movements. The researchers discovered they could predict stock market movements with a sizable degree of accuracy using a mood-based model derived from Twitter data. However, given the dynamic nature of financial markets and other factors affecting stock prices, the study emphasizes the need for in-depth analysis beyond Twitter sentiment alone. Therefore, correlation scores should be one of many considerations when making investment decisions, even though they shed light on the relationship between CEO tweets and stock market prices. Before making wise investment decisions, it is essential to consider additional factors such as financial reports, industry trends, and market conditions.

Linear Discriminant Analysis

The classification metrics for Linear Discriminant Analysis are shown in Table 4. Based on the CEO's tweet, the study used Linear Discriminant Analysis to predict whether a stock price would increase or decrease.

Table 4

Classification Metrics for Linear Discriminant Analysis

CEO	Accuracy	Precision	Recall	F1-score
Tim Cook (Apple)	1.00	1.00	1.00	1.00
Jeff Bezos (Amazon)	0.94	0.95	0.91	0.93
Sundar Pichai (Google)	0.92	0.89	0.95	0.92
Satya Nadella (Microsoft)	0.99	1.00	0.99	1.00
Elon Musk (Tesla)	0.82	0.98	0.65	0.78

The results of the linear discriminant model for predicting the direction of stock prices for companies of different CEOs show that the model performs well for some CEOs rather than others. Overall, the model achieves a high accuracy score, which suggests correctly classifying the direction of stock prices for most companies. A study conducted by You, Y., Srinivasan, S., Pauwels, K. et al. (2020) stated that CEO characteristics and traits affect demographics and change as time passes as the market processes the implications of various CEO factors.

The model's highest accuracy scores are for Tim Cook and Satya Nadella, with scores of 1.0, indicating that the model correctly predicts the direction of the stock prices for Apple and Microsoft, respectively. Jeff Bezos also has a high accuracy score of 0.94, indicating that the model is classifying the stock price direction for Amazon with high accuracy.

The model demonstrates strong performance in predicting the direction of stock prices for most CEOs. While the accuracy scores for Sundar Pichai and Elon Musk are lower, they are still relatively high, with scores of 0.92 and 0.82, respectively, indicating that the model can accurately classify the direction of stock prices for these companies as well.

For precision, the model achieves high scores for all CEOs, indicating that the model makes few false positive predictions. This is an essential metric for stock price classification, as false positives can be costly for investors who make decisions based on these classifications.

The recall score, on the other hand, is more varied across the different CEOs. The model achieves a perfect recall score of 1.0 for Tim Cook and Satya Nadella, indicating that the model correctly classifies the direction of the stock prices for all the instances where the prices went up or down. Sundar Pichai and Jeff Bezos's recall scores are slightly lower but still relatively high, at 0.95 and 0.91, respectively. However, the model struggles with recall for Elon Musk, with a score of 0.65, indicating that the model needs to be accurately predicting the direction of the stock prices for Tesla due to the low correlation between Elon Musk's tweets and the Tesla stocks.

Finally, the F1-score, which measures precision and recall, is also relatively high for all CEOs except Elon Musk. This suggests that the model is performing well for most companies but needs help to predict the direction of stock prices for Tesla accurately.

Overall, the results suggest that the linear discriminant model performs well in classifying the direction of stock prices for most CEOs. Still, some CEOs, particularly Elon Musk, have room for improvement.

Conclusion

In summary, this study investigated the effects of the Twitter use of CEOs on their company's stock prices and stock market activity. The results showed that the impact of the sentiments of Twitter posts on the stock prices varied among the different CEOs. In relation, some CEOs, such as Jeff Bezos, have Twitter activities that have more influence on their company's stock prices than the other CEOs. However, despite the effects of the CEO's Twitter activity, the positive impact of their Twitter use makes only a small and limited difference. The linear discriminant analysis also shows strong performance in predicting the direction of stock prices for most CEOs, achieving high accuracy and precision scores. In conclusion, the linear discriminant analysis algorithm performs well for predicting stock market performance based on CEOs' tweets but has room for improvement.

Limitations and Recommendations for Future Research

This study only focused on the CEOs' Twitter posts to investigate the relationship between their Twitter activity and the performance of their company's stocks. For future study, the sentiments of the replies from CEO tweets can be further explored to understand the CEOs' Twitter activity and how the engagements in their account could also affect stock market performance. Another limitation of this paper is that only some CEOs have a Twitter account or are active in using Twitter. The researchers suggest further investigating the CEOs' social media activities on other platforms.

Another prospective study could include the effect of the CEOs' sentiments in video streaming social media applications, including the CEOs' public appearances on social media, on the stock market's performance.

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