






# Impact of Twitter on Stock Market Performance: Evidence from Elon Musk and Tesla

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**Abstract.** In the last decade, rising social media impact along with technological progress has given the potential for higher “democratization” of public voice. However, influential individuals, with hundreds of millions followers got the possibility to shape the public opinion and create herding behavior. Twitter activities, especially with financial markets-related content are gaining popularity as well. In that regard, the purpose of the paper is to analyze correlation between Elon Musk’s Twitter activities and stock price performance of Tesla company, by using different models of sentiment analysis. Rapid Automatic Keyword Extraction tool was used in Phyton. Correlation analysis was done for the 3-year time period (Oct 2019–Oct 2022) in order to capture heightened volatility and various systematic risks, which had resulted in even more tweeting activities. Results showed that there is mid to high correlation between Elon Musk’s tweets and share price of Tesla.

**Keywords:** Twitter · stock market · Elon Musk · Tesla · sentiment analysis

## 1 Introduction

As one of the defining features of modern financial markets, informational function has the profound role in determining the forecasting reliability and relevance, as well as the necessary tool in projecting future investing and financing activity. Some of the pioneered research with respect to informational role and its predicting ability are based on the random walk theory and efficient market hypothesis (EMH), which were the markets’ paradigm in the coming decades [2, 4]. Given the unpredictable nature of new information, stock markets can’t be predicted with certain reliability. However, with the rising importance of behavioral economics and finance, conventional paradigms have to be altered and enriched with the new findings where financial decisions are driven by emotions and mood, and not merely by the utility function and rational decision-making process [3, 7, 10]. That having in mind, assumptions can be made that the public mood and sentiment can impact stock markets as much as news.

The rising significance of social media in everyday life of individuals, as well as in private and public sector, have created the derived role of platforms which can have an

impacting effect on financial markets as well. In that regard, Twitter social network has been showing increasing importance in creating and influencing public opinion in various areas, including the stock markets with its sentiment analysis. During the presidential mandate of Donald Trump, Twitter has been the leading communication channel for US President, and it has also started to be the analytical tool for evaluating financial markets post-actions [8]. Although its user base is not (yet) in the top ten social media rankings, with more than 300 million accounts, its outreach and impact is much greater than with the others, given its design nature, marketing influence and other characteristics. Some of those accounts are having tens of millions followers, thus having enormous outreach and ability to form the public opinions and actions. As one of the most influential Twitter account holders, with more than 100 million followers (Socialtracker.io, 2022), Elon Musk has been witnessing rising interest with respect to his tweets and subsequent actions in the financial markets. This is predominantly visible in his tweets related to Tesla company and, lately, to the “Twitter saga” of company buyout and turning it into private equity. Starting from 2009 Musk had almost 20 thousand tweets.

In this paper we analyze the relationship between Musk’s tweets and Tesla stock price, with respect to correlation analysis, and using several Python libraries so we would be able to quantify Twitter content and correlate it to stock prices. It should not be overseen the fact that Musk is the owner and investment angel in several other companies, public and private ones, and anything happening in one of those companies is reflected in the price of others. Additionally, this paper analyses Tesla’s stock prices from the end of 2019. When Corona virus took its swing, people were spending more time at home, consuming less of its discretionary income and saving more money, accompanied with several rounds of work.

The paper is organized as follows: Sect. 2 discusses relevant literature body followed by methodological approach and accompanying results and discussion in Sect. 3. Paper concludes with a summary of results and further research possibilities in Sect. 4.

## 2 Literature Review

The contemporary nature of this topic is demonstrated, among other things, with the young research body in the academic literature. One of the pioneered work where Twitter activity was associated with stock market performance was done by Bollen, Mao and Zeng [1] where the authors correlated collective Twitter mood with the performance of DJIA (Dow Jones Industrial Average) then fed into a neural network to predict market movement. They concluded that public mood states, as measured by the sentiment analysis software - OpinionFinder and Google-Profile of Mood States (GPOMS) are predictive of changes in DJIA closing values, with the accuracy of 86.7% in predicting the daily up and down changes in the closing values of the DJIA. With the focus of Twitter being communication channel Sprenger et al. [13] investigated how different company-specific news published on Twitter are related to S&P 500 stock prices. The results showed that the content of Twitter messages provides valuable information with regard to the effects of stock-related news on company financial indicators.

One of the first studies that addressed specific stock-related Twitter activities and their impact on stock market performance was done by Sprenger et al. [13] where the

authors used microblogging messages on a daily basis, and examined the relationship between tweet features and the corresponding market features return, trading volume, and volatility. Significant association was found between tweet sentiment and stock returns and message volume with the trading volume. Zhang [14] performed different machine learning techniques on positive or negative sentiment on a tweet corpus, with the emphasis on specific keywords, with the more relevance on negative sentiment and correlation.

Tweeter activities were associated with specific group of nine IT companies in Garcia Lopez et al. [5] with the correlation between the amount of daily messages and the volume of financial transactions. The results also showed that messages generated during a positive, negative and neutral trend can be classified in the sense that stock market performance has an impact on social media topics. Smailovic et al. [11] used Granger causality test and adapted the Support Vector Machine classification mechanism to categorize tweets into three sentiment categories (positive, negative and neutral), resulting in significance of sentiment polarity (positive and negative sentiment) as an indicator of stock price movements a few days in advance.

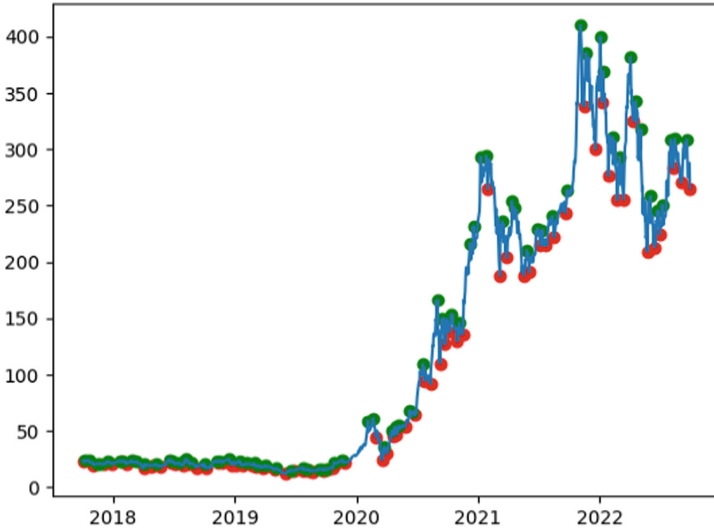
When it comes specifically to Elon Musk and his Twitter activities, similar work was done by Kang Kim et al. [6] where the authors investigated specific connection between his account and the stock value of Tesla. They performed sentiment analysis by using different Machine Learning algorithms, such as Logistic Regression and Support Vector Machine. The results were in favor of distinct correlation: an increase in the number of tweets/engagement would lead to an increase in the closing price of Tesla, as well as vice versa.

### 3 Methodology and Results

Daily stock price data for Tesla was taken from Yahoo Finance Python library, for the 3-year period between 01.10.2019 and 01.10.2022. This period is characterized by several major systematic events (outbreak of Covid-19, lockdowns, economic reopening and geopolitical conflicts) which have caused unprecedented stock price volatility, relative to more stable period prior the 2019 (Graph 1). When it comes to company itself, launching of the SpaceX satellites and significant inside selling activity from Elon Musk with respect to funding of Twitter acquisition were significant influencing factors to stock performance.

Other input in the analysis - Twitter data includes Elon Musk's Tweets up to five days before major change in share price, number of likes and shares of these tweets, as well as those tweets where Tesla as a company was specifically mentioned. For each price change, Tweets for the last five days are merged into single text based on the day which represents the basis for further refinement (Table 1).

For the keyword extraction Rake algorithm (Rapid Automatic Keyword Extraction algorithm) was used. RAKE is calculating keyword by taking ratio of degree to frequency or words. It is used for extracting keywords from any text. RAKE gives us options of excluding stop words, words like "a", "the", "about", or words that are commonly used in text and based on frequency can be given higher weight. In order to perform sentiment analysis we used TextBlob Python library. When computing a sentiment for a single



**Fig. 1.** Tesla share price over time

**Table 1.** Elon Musk Tweet society response

Year	Avg. Number of likes	Avg. Number of reshares
2019	116241	16722
2020	164552	10175
2021	736097	71614
2022	739945	55298

word, TextBlob employs the “averaging” technique, which is applied to polarity values to calculate a polarity score for a single word, and thus a similar procedure applies to every single word, resulting in a combined polarity for larger texts (Analyticsindiamag.com, 2022). For dataset we took minimums and maximums of share prices based on the ten day time span window.

We used keyword extraction for giving weight to the Tweet and we used sentiment analysis to give it direction. After extracting keywords and context, we performed several tests to decide which past days we need to give more consideration and to find Tweets that are impacting share price change. After several iterations, including and excluding stop words, with and without Tesla being mentioned specifically, we came to conclusion that the most impactful are the Tweets without stop words and Tesla being mentioned (Table 2).

After seeing the matrix, we can observe presence of correlation between Musk’s tweets and share price of Tesla. This correlation is on the verge between medium and high level. Given the fact that Elon Musk ownership is in decreasing trend (with 15%

**Table 2.** Correlation matrix for Tweets made one day before major price change

	Price change (%)	Abs. Price change	Price change trend
Trend sentiment	0.274338	0.270842	0.143614
Avg. weight of keyword for D1	0.162493	0.28185	0.04911
Sentiment of D1	0.309077	0.458214	0.159411
Impact	0.309343	<b>0.50062</b>	0.178058

Source: The authors' calculation

of company's shares) real impact is even higher. That can be attributed to very strong influential capacity of Elon Musk, especially among large community of retail investors (almost 80% of ownership belongs to them) who are driven by his role model status and other behavioral factors.

## 4 Conclusion

Financial markets are exhibiting unprecedented times in the last three years. Heightened volatility, abnormal returns and widespread usage penetration among retail investors have led to extreme market sentiment where the fraction of news or even the frequent rumors are leading to overreactions, in both ways. This scenario has opened the doors to social media to become *vox populi* of different types of investors. Among many social media, Twitter platform deserves special attention, due to its outreach power and mainstream relevance. In that regard, messages being communicated through tweets can have (un)expectedly powerful effect, and with the different goals.

In this paper different tests of sentiment analysis were applied along with the keyword extraction tools. Results have indicated that Twitter and Twitter posts can be used for improvement in stock price prediction models by using NLP and general sentiment analysis. This paper can be upgraded with more variables and more precise sentiment analysis models. This study also shows that stock market could be potential conduit for manipulated activities or affected by a very few influential people and social media. It should be explored how, in what way and to what extent people who are perceived as influential can affect global market.

## References

1. Bollen, J., Mao, H., Zeng, X. (2011) Twitter mood predicts the stock market, *Journal of Computational Science*, Volume 2, Issue 1, Pages 1–8, ISSN 1877-7503, <https://doi.org/10.1016/j.jocs.2010.12.007>
2. Cootner P, H. *The Random Character of Stock Market Prices*, MIT, 1964.
3. Damasio, A. R.: *Descartes error: emotion, reason, and the human brain*. Harper Perennial (1995)
4. Fama, E., Fischer, L., Jensen, M.C., Roll, R. The adjustment of stock prices to new information, *International Economic Review* 10 (February (1)) (1969) 1–21, <http://ideas.repec.org/a/ier/iecrev/v10y1969i1p1-21.html>.

5. Garcia-Lopez, F.J. Batyrshin, I., and Gelbukh, A. (2018) Analysis of relationships between tweets and stock market trends, *Journal of Intelligent & Fuzzy Systems* 34 pp. 3337–3347, <https://doi.org/10.3233/JIFS-169515>
6. Kang Kim, D.P., Lee, J., Lee, J., Suh, J. (2021) Elon Musk's Twitter and Its Correlation with Tesla's Stock Market. *International Journal of Data Science and Analysis*. Vol. 7, No. 1, pp. 13–19. <https://doi.org/10.11648/j.ijdsa.20210701.14>
7. Kavussanos, M., Dockery, E.A.: Multivariate test for stock market efficiency: The case of ASE. *Applied Financial Economics*, 11(5), 573–579 (2001)
8. Machus, T., Mestel, R., Theissen, E. Heroes, just for one day: The impact of Donald Trump's tweets on stock prices, *Journal of Behavioral and Experimental Finance*, Volume 33, 2022, 100594, ISSN 2214-6350, <https://doi.org/10.1016/j.jbef.2021.100594>.
9. Mendoza-Urdiales, R.A., Núñez-Mora, J.A., Santillán-Salgado, R.J.; Valencia-Herrera, T. Twitter Sentiment Analysis and Influence on Stock Performance Using Transfer Entropy and EGARCH Methods. *Entropy* 2022, 24, 874. <https://doi.org/10.3390/e24070874>
10. Nofsinger, J. R.: Social Mood and Financial Economics. *Journal of Behavioral Finance*, 6(3), 144–160 (2005)
11. Smailović, J., Grčar, M., Lavrač, N., Žnidaršič, M. (2013). Predictive Sentiment Analysis of Tweets: A Stock Market Application. In: Holzinger, A., Pasi, G. (eds) *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data*. HCI-KDD 2013. *Lecture Notes in Computer Science*, vol 7947. Springer, Berlin, Heidelberg. [https://doi.org/10.1007/978-3-642-39146-0\\_8](https://doi.org/10.1007/978-3-642-39146-0_8)
12. Sprenger, T., Tumasjan, A., Sandner, P.G., and Welpel (2014) I.M. Tweets and Trades: the Information Content of Stock Microblogs, *European Financial Management*, Vol. 20, No. 5, 2014, 926–957, <https://doi.org/10.1111/j.1468-036X.2013.12007.x>
13. Sprenger, T.O., Sandner, P.G., Tumasjan, A. and Welpel, I.M., 'News or noise? The stock market reaction to different types of company-specific news events.' Working Paper (Technische Universität München, TUM School of Management, 2012).
14. Zhang, L. (2013) Sentiment analysis on Twitter with stock price and significant keyword correlation, The University of Texas Scholar Works, Department of Computer Sciences, Honors Theses, <http://hdl.handle.net/2152/20057>
15. <https://analyticsindiamag.com/how-to-obtain-a-sentiment-score-for-a-sentence-using-tblob/>, Date accessed: 19.10.2022. Social tracker, available on: [https://www.socialtracker.io/toplists/top-50-twitter-users-byfollowers/#google\\_vignette](https://www.socialtracker.io/toplists/top-50-twitter-users-byfollowers/#google_vignette) (Date accessed: 19.10.2022)

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