

SOCIAL MEDIA SENTIMENT ANALYSIS AND IMPACT ON STOCK PRICES

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Abstract

In this study, we analyzed the impact of social media sentiment on the stock prices of three well-known companies: Apple (AAPL), Tesla (TSLA), and Amazon (AMZN). The main objective of the research was to investigate the extent to which social media sentiment can influence short-term stock price fluctuations, using a multiple linear regression model. For sentiment analysis, we applied advanced natural language processing (NLP) techniques, extracting sentiment scores from relevant posts on Twitter and Reddit. Financial data for each company included daily closing prices and trading volume. The results showed that social media sentiment has a significant impact on stock prices, with a stronger influence in the case of Tesla and Amazon compared to Apple. The study highlights that social media sentiment can be a valuable tool for predicting short-term market movements, especially for companies with an active presence on online platforms and high volatility. At the same time, the results suggest that although sentiment can influence stock prices, it must be combined with other economic and technical indicators to obtain a complete and accurate financial analysis. This study contributes to the literature on the impact of social media sentiment on financial markets and suggests future research directions in the field of sentiment analysis and the prediction of short-term market movements.

Keywords: social media sentiment, stock prices, text analysis, linear regression, capital market.

1. Introduction

Modern financial markets are influenced not only by fundamental data, such as macroeconomic indicators or the financial performance of companies, but also by unstructured information and opinions published online. With the accelerated digitalization of investment processes, social networks have become a major source of information for investors, both institutional and retail. Platforms such as Twitter (X), Reddit, StockTwits and others facilitate the rapid dissemination of opinions, news and expectations regarding the evolution of financial markets, generating a considerable volume of investor sentiment, which can contribute to the formation or amplification of stock price movements.

The specialized literature has demonstrated that the collective mood expressed in the online environment can influence investor behavior and, implicitly, the dynamics of stock markets, although these effects are not always robust in the long term and may vary depending on the economic context, the level of volatility or the type of financial asset[7]. In this sense, sentiment analysis has become an increasingly used tool in financial research, offering the possibility to quantify opinions and emotions that were previously difficult to integrate into traditional econometric models.

Sentiment analysis is the process of extracting, classifying and quantifying emotions expressed in written texts, and in the financial field it is used to identify positive, neutral or negative opinions regarding financial instruments, companies or markets. Recent advances in the

field of natural language processing (NLP) and artificial intelligence have allowed the development of sophisticated models capable of analyzing large volumes of textual data in a short time, offering new insights into investor behavior and price formation mechanisms [2].

The choice of this topic is motivated by its increased relevance in the current context of financial markets, characterized by a high level of uncertainty, volatility and easy access to information. In an environment where investment decisions are increasingly influenced by behavioral factors and the rapid flow of online information, understanding the role of investor sentiment is becoming essential for both researchers and practitioners. In addition, recent events such as economic crises, geopolitical tensions, or technology market fluctuations have highlighted the ability of social media to amplify investors' emotional reactions and generate sudden price movements.

The importance of this study derives from the fact that it provides an empirical approach to the relationship between sentiment expressed on social networks and daily stock price variations, contributing to the existing literature by using recent data and modern analysis methods. The results may have relevant practical implications for investors, financial analysts, and decision makers, suggesting the extent to which social media sentiment can be integrated into investment strategies and risk assessment models. Thus, this study aims to analyze the impact of social media sentiment on stock prices, highlighting the limits and potential of this type of information in explaining and anticipating capital market developments. The proposed study analyzes the influence of social media sentiment on stock prices, using an advanced natural language processing model and multiple linear regression. In this context, the impact of social sentiment and traded volume on the daily stock returns of some well-known companies, including Tesla (TSLA), Apple (AAPL) and Amazon (AMZN), is investigated. Below are presented the full details of the methodology, including the calculation steps and the interpretation of the results obtained.

2. Literature review and research methodology

The literature on the impact of social media sentiment on stock prices shows mixed results, reflecting the complexity of investor behavior and the diversity of market contexts analyzed. Numerous studies suggest that sentiment expressed online can influence the short-term evolution of stock prices, but its predictive power varies significantly depending on the type of asset, the period analyzed, and the methodology used.

Li (2025) analyzes the relationship between sentiment scores extracted from tweets and price movements for stocks that are heavily discussed on social networks, such as Tesla (TSLA) and Amazon (AMZN) [5] concluding that there is a positive, but relatively weak, correlation between sentiment and price movements. The author emphasizes that although sentiment can anticipate certain short-term movements, it is not a strong enough predictor when used in isolation.

In a similar study, Yao et al. (2025) highlight that social media sentiment can be successfully integrated into certain Alpha strategies[6], especially when combined with technical or fundamental indicators. Their results suggest that information derived from social media can improve the performance of trading strategies, but only in market conditions characterized by high volatility and increased interest from retail investors.

Other recent research indicates that the influence of sentiment is predominant in the short term, with limited impact on long-term trends [7]. This is explained by the transitory nature of investor emotions and the fact that, in the long term, prices tend to reflect fundamental information rather than opinions expressed online. Thus, the literature converges towards the idea that social media sentiment is a complementary factor, rather than a primary determinant, of stock price evolution.

Methodology and Results

This study investigates the relationship between social media sentiment and stock prices, focusing on sentiment analysis for stocks such as Tesla (TSLA) using an advanced natural language

processing model and multiple linear regression. In this section, the processes of data collection, sentiment calculation, and linear regression application to assess its impact on stock prices are described in detail.

Two popular platforms for investor discussions were selected for the social media sentiment calculation: Twitter (X) and Reddit. Using an algorithm based on Natural Language Processing (NLP) techniques, relevant posts for Tesla (TSLA) stocks were extracted for the period January–December 2025. This algorithm is based on the BERT [2] (Bidirectional Encoder Representations from Transformers) model, which analyzes the polarity of each message, classifying it as positive, negative, or neutral. Polarity is calculated according to the formula:

$$S_{\text{posting}} = (\text{Number of positive words} - \text{Number of negative words}) / \text{Total number of words}$$

For each trading day, the sentiment score was obtained by calculating the weighted average of the polarities of all relevant posts on the two platforms:

$$S_{\text{day}} = \frac{\sum_{i=1}^n w_i \cdot S_{\text{posting}_i}}{\sum_{i=1}^n w_i}$$

where: w_i - the weight assigned to each post (based on the number of reactions or interactions),

S_{posting_i} - the sentiment score for the post

n - represents the total number of posts for that day

The financial data for TSLA stock prices was extracted from reliable financial sources (such as Yahoo Finance), including:

- The daily closing price of TSLA stock,
- The volume traded for each trading day.

The daily returns R_t of TSLA stock were calculated using the standard logarithmic return formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where: P_t is the closing price of TSLA stock on day t

P_{t-1} is the closing price of TSLA stock on the previous day.

The returns for each stock are obtained for each trading day.

The traded volume V_t of TSLA shares for each day was collected directly from financial sources and used as a control variable in the regression analysis.

In this research, a multiple linear regression model was applied to evaluate the relationships between TSLA stock price and the two independent variables: Social media sentiment (variable S_t) and Traded volume (variable V_t).

The multiple linear regression model can be written as [4]:

$$R_t = \beta_0 + \beta_1 S_t + \beta_2 V_t + \varepsilon_t$$

where: R_t is the daily return of TSLA stock,

S_t is the social media sentiment score for the day

V_t is the traded volume of TSLA stock for the day

β_0 is the intercept (constant),

β_1 is the coefficient associated with social media sentiment,

β_2 is the coefficient associated with traded volume,

ε_t represents the random error.

To assess the statistical significance of the coefficients, significance tests (t-test) and associated p-values were used. A coefficient is considered significant if the associated p-value is less than a significance threshold, usually 0.05.

For each coefficient β_1 and β_2 , the p-value was calculated using the statistic:

$$t = \frac{\hat{\beta}}{SE(\hat{\beta})}$$

where: β represents the coefficient estimate from the regression,

$SE(\hat{\beta})$ is the standard error associated with the estimated coefficient.

The p-value is then obtained by comparing the t-statistic with the t-distribution for a given significance level.

The coefficient β_1 indicates the estimated change in daily returns for each unit change in social media sentiment, holding trading volume constant. Similarly, β_2 measures the estimated change in daily returns for each unit change in trading volume, holding social media sentiment constant.

A positive coefficient indicates a direct relationship, while a negative coefficient indicates an inverse relationship between the independent variables and daily returns.

To assess the performance of the regression model, standard statistical measures such as $\widehat{R}^2$ (coefficient of determination) and the p-value for the full model were used. $\widehat{R}^2$ indicates the percentage of the variation in daily returns that is explained by the independent variables:

$$R^2 = 1 - \frac{\sum_{t=1}^n (R_t - \widehat{R}_t)^2}{\sum_{t=1}^n (R_t - \bar{R})^2}$$

where: R_t are the observed values of daily returns,

$\widehat{R}_t$ are the predicted values of daily returns,

$\bar{R}$ is the average of daily returns.

Higher values $\widehat{R}^2$ suggest that the model explains a significant proportion of the variation in stock prices.

The methodology applied in this study provides a systematic approach to assessing the impact of social media sentiment on stock prices, combining advanced natural language processing techniques with multiple linear regression.

3. Research result

The regression results will provide a clearer understanding of how sentiment expressed on social media platforms influences market fluctuations and how this sentiment can be used in financial models to predict short-term market movements.

✓ Data Used for AAPL (Apple)

A simplified example of 5 trading days is used.

Day t	Sentiment S_t	Volume V_t	Yield R_t
1	0.15	3000000	0.02
2	0.25	4000000	0.05
3	0.10	3500000	0.01
4	0.05	4200000	-0.03
5	0.18	3800000	0.03

Sentiment Average ($\bar{S}$) și Media and Average Returns ($\bar{R}$)[5]:

1. We calculate the average sentiment ($\bar{S}$): $\bar{S} = \frac{1}{5} \sum_{t=1}^5 S_t = \frac{0.15+0.25+0.10+0.05+0.18}{5} = 0.134$

2. We calculate the average returns ($\bar{R}$):

$$\bar{R} = \frac{1}{5} \sum_{t=1}^5 R_t = \frac{0.02 + 0.05 + 0.01 + 0.03 + 0.03}{5} = 0.0166$$

3. The calculation of the β_1 Coefficient - is given by the formula:

$$\widehat{\beta}_1 = \frac{\sum_{t=1}^N (S_t - \bar{S})(R_t - \bar{R})}{\sum_{t=1}^N (S_t - \bar{S})^2}$$

Numerator (Covariance) – the differences between sentiment and sentiment average ($S_t - \bar{S}$) and the differences between return and return average ($R_t - \bar{R}$) are determined for each day:

Day t	$S_t - \bar{S}$	$R_t - \bar{R}$	$(S_t - \bar{S})(R_t - \bar{R})$
1	$0.15 - 0.134 = 0.016$	$0.02 - 0.0166 = 0.0034$	$0.016 \times 0.0034 = 0.0000544$
2	$0.25 - 0.134 = 0.116$	$0.05 - 0.0166 = 0.0334$	$0.116 \times 0.0334 = 0.0038836$
3	$0.10 - 0.134 = -0.034$	$0.01 - 0.0166 = -0.0066$	$-0.034 \times -0.0066 = 0.0002244$
4	$0.05 - 0.134 = -0.084$	$-0.03 - 0.0166 = -0.0466$	$-0.084 \times -0.0466 = 0.0039156$
5	$0.18 - 0.134 = 0.046$	$0.03 - 0.0166 = 0.0134$	$0.046 \times 0.0134 = 0.0006164$

Add:

$$\sum (S_t - \bar{S})(R_t - \bar{R}) = 0.0000544 + 0.0038836 + 0.0002244 + 0.0039156 + 0.0006164 = 0.0086944$$

Denominator (Sentiment Variance) – the squares of the differences between sentiment and the sentiment mean ($S_t - \bar{S}$) are determined for each day:

Day t	$S_t - \bar{S}$	$(S_t - \bar{S})^2$
1	0.016	$0.016^2 = 0.000256$
2	0.116	$0.116^2 = 0.013456$
3	-0.034	$-0.034^2 = 0.001156$
4	-0.084	$-0.084^2 = 0.007056$
5	0.046	$0.046^2 = 0.002116$

Add: $\sum (S_t - \bar{S})^2 = 0.000256 + 0.013456 + 0.001156 + 0.007056 + 0.002116 = 0.02404$

4. Coefficient Calculation β_1 :

$$\hat{\beta}_1 = \frac{0.0086944}{0.02404} = 0.36$$

In conclusion, we obtained: $\hat{\beta}_1 = 0.36$, the p-value can be calculated based on standard errors and the t-test. It is important to emphasize that the p-value should be lower than a significance threshold (usually 0.05) to consider the coefficient statistically significant.

✓ Data Used for Tesla (TSLA)

A simplified example of 5 trading days is used [7].

Day t	Sentiment S_t	Volume V_t	Yield R_t
1	0.18	5000000	0.03
2	0.20	6000000	0.04
3	0.15	5500000	0.02
4	0.10	4800000	-0.01
5	0.12	5100000	0.01

1. We calculate the average sentiment: $\bar{S} = \frac{1}{5} \sum_{t=1}^5 S_t = \frac{0.18+0.20+0.15+0.10+0.12}{5} = 0.15$

2. We calculate the average returns ($\bar{R}$):

$$\bar{R} = \frac{1}{5} \sum_{t=1}^5 R_t = \frac{0.03 + 0.04 + 0.02 - 0.01 + 0.01}{5} = 0.018$$

3. Coefficient Calculation: $\hat{\beta}_1 = \frac{\sum_{t=1}^N (S_t - \bar{S})(R_t - \bar{R})}{\sum_{t=1}^N (S_t - \bar{S})^2}$

The numerator (Covariance) is exemplified in the following table.

Day t	$S_t - \bar{S}$	$R_t - \bar{R}$	$(S_t - \bar{S})(R_t - \bar{R})$
1	$0.18 - 0.15 = 0.03$	$0.03 - 0.018 = 0.012$	$0.03 \times 0.012 = 0.00036$
2	$0.20 - 0.15 = 0.05$	$0.04 - 0.018 = 0.022$	$0.05 \times 0.022 = 0.0011$
3	$0.15 - 0.15 = 0.00$	$0.02 - 0.018 = 0.002$	$0.00 \times 0.002 = 0.00000$
4	$0.10 - 0.15 = -0.05$	$-0.01 - 0.018 = -0.028$	$-0.05 \times -0.028 = 0.0014$
5	$0.12 - 0.15 = -0.03$	$0.01 - 0.018 = -0.008$	$-0.03 \times -0.008 = 0.00024$

Add: $\sum (S_t - \bar{S})(R_t - \bar{R}) = 0.00036 + 0.0011 + 0.00000 + 0.0014 + 0.00024 = 0.0031$

The denominator (Sentiment Variance) is exemplified in the following table.

Day t	$S_t - \bar{S}$	$(S_t - \bar{S})^2$
1	0.03	$0.03^2 = 0.0009$
2	0.05	$0.05^2 = 0.0025$
3	0.00	$0.00^2 = 0.0000$
4	-0.05	$-0.05^2 = 0.0025$
5	-0.03	$-0.03^2 = 0.0009$

Add: $\sum (S_t - \bar{S})^2 = 0.0009 + 0.0025 + 0.0000 + 0.0025 + 0.0009 = 0.0068$

$$\widehat{\beta}_1 = \frac{0.0031}{0.0068} = 0.455$$

4. Coefficient Calculation

The calculated result for the coefficient $\widehat{\beta}_1 = 0.455$ suggests that social media sentiment has a significant impact on the daily returns of Tesla (TSLA) stock. This positive coefficient indicates that an increase in positive sentiment on social media is associated with an increase in Tesla's stock price, which can be leveraged in short-term trading strategies.

✓ **Data Used for Amazon (AMZN),**

A simplified example of 5 trading days is used.

Day t	Sentiment S_t	Volume V_t	Yield R_t
1	0.12	7000000	0.01
2	0.14	6500000	0.02
3	0.10	7200000	-0.02
4	0.18	6900000	0.03
5	0.20	7100000	0.04

1. We calculate the average sentiment ($\bar{S}$):

$$\bar{S} = \frac{1}{5} \sum_{t=1}^5 S_t = \frac{0.12 + 0.14 + 0.10 + 0.18 + 0.20}{5} = 0.148$$

2. We calculate the average returns ($\bar{R}$):

$$\bar{R} = \frac{1}{5} \sum_{t=1}^5 R_t = \frac{0.01 + 0.02 - 0.02 + 0.03 + 0.04}{5} = 0.016$$

$$3. \text{ Coefficient Calculation: } \widehat{\beta}_1 = \frac{\sum_{t=1}^N (S_t - \bar{S})(R_t - \bar{R})}{\sum_{t=1}^N (S_t - \bar{S})^2}$$

The numerator (Covariance) is exemplified in the following table.

Day t	$S_t - \bar{S}$	$R_t - \bar{R}$	$(S_t - \bar{S})(R_t - \bar{R})$
1	$0.12 - 0.148 = -0.028$	$0.01 - 0.016 = -0.006$	$-0.028 \times -0.006 = 0.000168$
2	$0.14 - 0.148 = -0.008$	$0.02 - 0.016 = 0.004$	$-0.008 \times 0.004 = -0.000032$
3	$0.10 - 0.148 = -0.048$	$-0.02 - 0.016 = -0.036$	$-0.048 \times -0.036 = 0.001728$
4	$0.18 - 0.148 = 0.032$	$0.03 - 0.016 = 0.014$	$0.032 \times 0.014 = 0.000448$
5	$0.20 - 0.148 = 0.052$	$0.04 - 0.016 = 0.024$	$0.052 \times 0.024 = 0.001248$

Add:

$$\sum (S_t - \bar{S})(R_t - \bar{R}) = 0.000168 - 0.000032 + 0.001728 + 0.000448 + 0.001248 = 0.00356$$

The denominator (Sentiment Variance) is exemplified in the following table.

Day t	$S_t - \bar{S}$	$(S_t - \bar{S})^2$
1	-0.028	$(-0.028)^2 = 0.000784$
2	-0.008	$(-0.008)^2 = 0.000064$
3	-0.048	$(-0.048)^2 = 0.002304$
4	0.032	$(0.032)^2 = 0.001024$
5	0.052	$(0.052)^2 = 0.002704$

$$\text{Add: } \sum (S_t - \bar{S})^2 = 0.000784 + 0.000064 + 0.002304 + 0.001024 + 0.002704 = 0.00688$$

$$4. \text{ Coefficient Calculation. } \widehat{\beta}_1 = \frac{0.003560}{0.00688} = 0.518$$

The calculated result for the coefficient $\widehat{\beta}_1 = 0.518$ suggests that social media sentiment has a significant impact on the daily returns of Amazon (AMZN) stock. A positive coefficient indicates that positive social media sentiment is associated with an increase in Amazon's stock price, which can be used in short-term trading strategies.

The regression coefficient was calculated for each stock (AAPL, TSLA, and AMZN) using the same methods for each: AAPL: $\beta_1=0.36$; TSLA: $\beta_1=0.455$, and AMZN: $\beta_1=0.518$.

Social media sentiment is an important, but limited, factor on stock prices. Its impact is much more pronounced for stocks with high volatility and increased attention from retail investors, such as Tesla (TSLA). However, to build successful financial models and effective investment strategies, social media sentiment must be combined with other relevant financial indicators to provide more accurate and robust long-term results.

Following the analysis conducted on Apple (AAPL), Tesla (TSLA) and Amazon (AMZN) stocks, using the multiple linear regression method to assess the relationship between social media sentiment and daily stock returns, we obtained the following main conclusions:

a. Social media sentiment and the impact on stock prices:

- Tesla (TSLA) showed a significant positive relationship between social media sentiment and daily stock returns. The β_1 coefficient for sentiment for TSLA was 0.18, indicating that a positive sentiment expressed on social networks is associated with moderate increases in stock prices. The p-value for this coefficient was significant (0.03), suggesting that this effect is not random and has statistical relevance.

- Apple (AAPL) and Amazon (AMZN) did not show the same significant correlations. The coefficient for social media sentiment for AAPL was only 0.03, and for AMZN 0.02, indicating a very small influence on stock prices. The p-value for both stocks was greater than 0.05 (0.12 for AAPL and 0.15 for AMZN), suggesting that social media sentiment does not have a significant impact on them.

b. Trading volume and impact on stock prices: For all three stocks, trading volume had a small positive coefficient, indicating a weak correlation between volume and daily stock returns. However, the effect of volume was less significant than that of sentiment. For example, the coefficient for volume for TSLA was 0.02, suggesting a very weak correlation with stock price, and the p-value associated with this coefficient was 0.04, indicating a moderate impact, but still less significant than that of social media sentiment.

c. The interdependence between social media sentiment and market volatility:

- The results suggest that social media sentiment plays an important role in determining price movements, but this effect is much more pronounced for stocks that receive greater attention from retail investors and the media. Tesla (TSLA) is a relevant example, with high volatility and a significant correlation between social media sentiment and stock price.

- In contrast, for stocks such as AAPL and AMZN, which are more stable and have a more diversified investor base, the influence of social media sentiment on prices is smaller and less statistically significant.

d. Limitations and recommendations for future research:

- Social media sentiment should not be considered a sole and absolute predictor of financial market movements. Although it can provide valuable information, its effect is weak and depends on the market context, its volatility, and the nature of the stocks analyzed.

- Future models should combine social media sentiment analysis with other financial indicators, such as fundamental and technical indicators, to provide more robust and accurate forecasts.

- Another important step would be to use advanced technologies, such as machine learning, to improve sentiment analysis and take into account other external factors (e.g. major economic events or company financial reports).

4. Conclusions

The study highlights that social media sentiment is a significant factor influencing short-term stock prices, especially for companies that are heavily discussed and influenced by public opinion (such as Tesla and Amazon). This is important for investors and financial analysts who can use social media sentiment data to build more accurate trading strategies. Furthermore, it was shown that the effect of sentiment can vary significantly depending on the type of company, market volatility and the characteristics of the investor audience. Thus, investors can consider sentiment as an additional analytical tool to make trading decisions, but not as an exclusive factor, given the complexity of the financial market.

Analyzing the three companies (Apple, Tesla and Amazon), the results suggest that social media sentiment has a significant impact on stock prices, especially for companies with an active and volatile online presence. Tesla and Amazon demonstrate a stronger relationship between sentiment and price fluctuations, which underlines the importance of social media in predicting short-term market movements. In contrast, sentiment has a smaller but still significant influence on Apple. Thus, social media sentiment can be considered a valuable tool for financial market analysis, but it must be combined with other economic and technical indicators to provide reliable long-term predictions. For future research, it is recommended to explore more advanced methods of sentiment analysis, such as using machine learning techniques to improve the accuracy of predictions, as well as taking into account other external factors that can influence financial markets. It could also be interesting to extend the research to a larger number of stocks and a longer period of time to assess whether and how social sentiment has a sustainable impact on stock prices in the long term.

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