AGORA International Journal of Economical Sciences, http://univagora.ro/jour/index.php/aijes
ISSN 2067-3310, E-ISSN 2067-7669
Vol. 18, No. 2 (2024), pp. 73-85

# MEDIA SENTIMENT AND STOCK PRICES: ANALYSING TEMPORAL DYNAMICS AND PREDICTIVE RELATIONSHIPS IN TESLA AND META

**L. ČIGILEIČIKAITĖ, G. GAILIŪTĖ, J. KARTAŠOVA**

**Laura Čigileičikaitė[1], Gabrielė Gailiūtė[2], Jekaterina Kartašova[3]**
[1 2 3] Business School of Vilnius University, Lithuania
[1] E-mail: laura.cigileicikaite@vm.stud.vu.lt
[2] E-mail: gabriele.gailiute@vm.stud.vu.lt
[3] E-mail: jekaterina.kartasova@vm.vu.lt, https://orcid.org/0000-0003-3774-1817

***Abstract:*** *The study investigates the relationship between media sentiment and stock price fluctuations. Using quantitative techniques, the research examines data from Tesla and Meta from 2019 to 2024. Headlines and adjusted stock prices were processed into monthly averages to reduce noise, enabling statistical analysis through cross-correlation and Granger causality tests. The results indicate a link between sentiment and stock prices, suggesting that sentiment may have some predictive capability for stock price movements. The research underscores the importance of addressing media sentiment in financial decision-making.*

***Keywords:*** *media sentiment, stock prices, cross-correlation, Granger causality*

## 1. INTRODUCTION

In today's digitized world, characterized by an overwhelming abundance of information, news and social media play an increasingly significant role in shaping public opinion. The media wield considerable influence over social attitudes, emotional responses, and decision-making processes through mechanisms such as agenda-setting, framing, priming, and emotional engagement, among others. This influence extends to financial markets, where investor behavior is often impacted by media narratives. Studies like Singh, Aggarwal, and Chauhan (2022) have demonstrated the power of sentiment analysis on social media platforms for predicting stock market trends. Building on these insights, this study focuses on sentiment from media headlines to evaluate its relationship with stock prices, extending sentiment analysis to professional sources. The rapid proliferation of digital platforms has further amplified the importance of understanding how media content shapes financial outcomes and decision-making processes. Fama (1970), in his foundational work on Efficient Market Hypothesis, posited that financial markets are "informationally efficient," implying that prices reflect all available information at any given time. However, the emergence of behavioral finance suggests that emotional factors, such as media sentiment, may cause deviations from efficiency. This study has two primary objectives: first, to examine whether media sentiment has a statistically significant relationship with adjusted stock closing prices; and second, to evaluate whether past sentiment data can predict future stock price trends. To achieve these goals, the study employs cross-correlation analysis and Granger causality tests, using sentiment data extracted from headlines scraped from Business Insider and stock price data retrieved through Python's yfinance library. The findings of this research aim to shed light on the complex interplay between media sentiment and stock prices, offering valuable insights into how sentiment influences market dynamics and investor behavior.

## 2. Summary of Research Design and Methods

This study explores the connection between media sentiment and corporate stock prices. It focuses on two globally recognized companies, Tesla and Meta, using data from *January 2019 to October 2024*. The research aims to evaluate correlation dynamics and test predictive capabilities.

## 3. Research Objective

The primary goal is to analyze whether media sentiment can influence or predict changes in stock prices. Similar studies have demonstrated the utility of sentiment analysis in understanding market trends, especially in emerging economies, where Mohan, Vemuri, and Mandal (2019) identified a significant relationship between sentiment shifts and financial market behavior. Their work focused on the unique dynamics of developing markets, so this research extends the analysis to high-visibility.

## 4. Study Sample and Analysis Period

Two companies — *Tesla* and *Meta* — were selected for their high visibility, strong market positions, and frequent media coverage. According to the information on CompaniesMarketCap website, Tesla, a leader in electric vehicles, had a market capitalization of $1.09 trillion in 2024. Its stock price fluctuated widely between $138.80 and $358.64, reflecting growth potential and volatility. Meta, valued at $1.49 trillion in 2024, represents innovation in artificial intelligence and virtual reality. Its stock price grew by 77% over the year, with forecasts predicting $575.93. These companies' media portrayal, often polarizing and dynamic, made them ideal for sentiment analysis.

The *January 2019–October 2024* timeframe provided a robust dataset for longitudinal analysis, covering significant global events such as the COVID-19 pandemic and geopolitical shifts. This aligns with other studies, which often rely on five-year periods to explore long-term patterns.

## 5. Data Sources, Collection and Processing

### Media Sentiment Data

Headlines from *Business Insider,* a leading financial and business news outlet, were chosen for their global reach and relevance. The platform's straightforward and well-structured HTML format facilitated efficient web scraping, enabling the extraction of approximately 35,000 headlines related to Tesla and Meta. These headlines were analyzed using the *VADER (Valence Aware Dictionary and Sentiment Reasoner)* model, a machine learning tool optimized for short text sentiment evaluation. The approach builds on methodologies from prior research, such as Loughran and McDonald (2011), who emphasized the importance of context-specific dictionaries for financial textual analysis. Their work demonstrated that sentiment analysis in financial contexts benefits from tailored linguistic tools to capture nuances in language.

Therefore, recent advancements in deep learning, as demonstrated by Xue (2023), have pushed the boundaries of sentiment analysis in financial markets. Xue's approach utilized advanced neural networks to capture complex patterns in sentiment data, enabling deeper insights into market behaviors. In addition, it was proposed in 2014 by C.J. Hutto and Eric Gilbert in their paper titled "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text". VADER computes positive, negative, neutral, and compound sentiment scores, making it suitable for analyzing headlines' emotional tones.

**Stock Price Data**

Stock prices were retrieved using Python's *yfinance* ***l***ibrary. Adjusted closing prices were chosen as the primary indicator because they account for corporate actions like dividends, stock splits, and market adjustments, offering a more accurate measure of stock value.

**Data Processing**

To reduce daily noise and emphasize trends, sentiment scores and adjusted closing price data were aggregated *into monthly averages*. Then temporal alignment between sentiment scores and stock prices was performed, enabling consistent statistical analysis.

## 6. Research Methods and Techniques

**Quantitative Analysis**

*Cross-Correlation Analysis*

Cross-correlation was used to examine the relationship between monthly sentiment scores and stock prices over time. This method identifies the strength and direction of associations at varying time lags, from *−6 months to +6 months*, revealing whether sentiment changes lead or lag behind stock price movements. Mohanty and Roy (2021) have demonstrated the effectiveness of cross-correlation in analyzing sentiment's influence on market trends, particularly for identifying leading or lagging relationships between variables. Their research underscores the importance of selecting appropriate time lags to uncover nuanced dynamics in sentiment-driven market behavior.

*Granger Causality Testing*

The Granger causality test evaluated whether past sentiment scores could predict future stock prices. This method is widely applied in financial studies to uncover predictive relationships between variables. As first developed by Granger (1969), the method assesses whether a time series provides statistically significant information about another series' future values. The Granger causality test was used to determine the predictive power of sentiment data on stock price movements for Tesla and Meta.

The suitability of these methods for similar studies is confirmed by the analysis conducted in V. Grigaitė's 2021 master's project, *"Analysis of the Relationships Between Macroeconomic Indicators and Stock Market Sectors,"* where they were successfully applied to identify connections between macroeconomic indicators and stock market sectors at the level of economic activity sectors in the United States.

## 7. Research Findings Overview

Preliminary results showed:

For Meta, the strongest correlation between sentiment scores and stock prices was observed with lags of 1–2 months. In contrast, for Tesla, a significant correlation was found only at a lag of 1 month, with correlation values at later lags proving to be insignificant.

## 8. Research Results

### Results of Quantitative Research Part

### Analysis of Time Series for Media Sentiment and Tesla Stock Price Averages

The initial examination of the relationship between Tesla's media sentiment and adjusted closing prices was conducted by analyzing two graphs.

**Figure 1**

*The monthly averages of sentiment scores for Tesla-related media coverage from* 2019 to October 2024

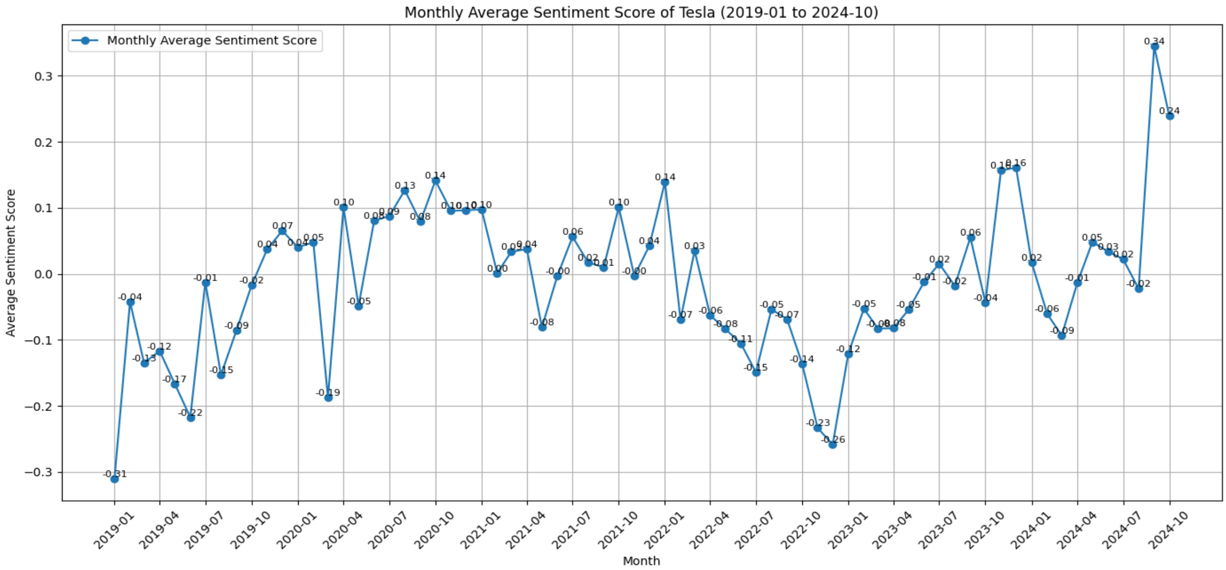
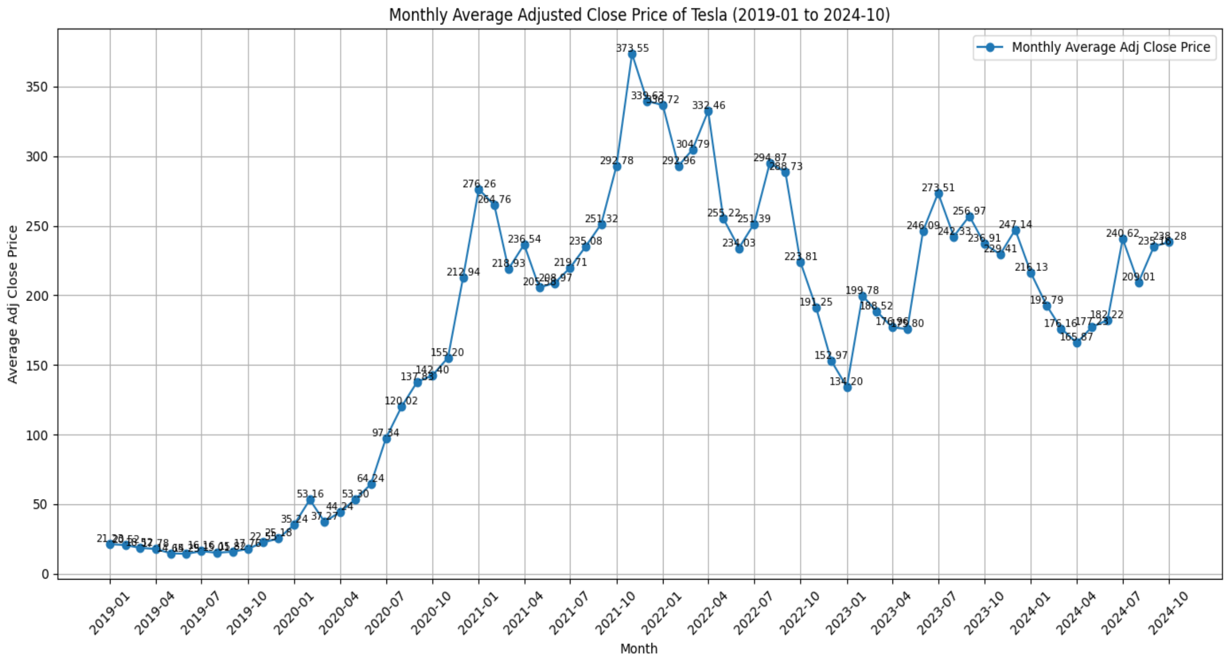



**Figure 2**

*The monthly averages of Tesla's adjusted closing stock prices from* 2019 to October 2024



The first chart presents the monthly average sentiment scores, while the second displays the monthly average stock adjusted closing prices. By analyzing both graphs, it was observed that during certain periods, the two variables—average sentiment scores and average stock prices—exhibited similar trends, moving in the same direction, either increasing or decreasing simultaneously. However, in other periods, the variables showed divergent movements. For instance, during certain months, sentiment scores rose while stock prices fell, and vice versa.

A preliminary analysis of the data reveals that in approximately 60% of the time periods, sentiment and stock prices exhibited a tendency to move in the same direction. This suggests a potential relationship between the two variables. However, the direction of the relationship was not consistently direct, as the two variables did not always move in parallel.

This observation provided the foundation for further analysis into a potential statistical relationship between media sentiment and stock prices. However, due to the complex and nonlinear nature of this relationship, further statistical testing was conducted using cross-correlation analysis and Granger causality tests, as traditional methods were deemed unsuitable for analyzing the observed dynamics.

**Cross-Correlation Results for Tesla Media Sentiment and Stock Price Averages**

The cross-correlation analysis was performed to determine the relationship between the monthly averages of Tesla's media sentiment scores and the company's average monthly adjusted closing prices at different time lags. The analysis aimed to assess whether there is a correlation between current sentiment and future stock prices, or if current stock prices influence future sentiment.

**Table 1:** *Cross-correlation values between Tesla's media sentiment scores and the company's adjusted closing prices*

| No | Time lags (in months) | Correlation values |
|---|---|---|
| 1 | -6 | -0.26613 |
| 2 | -5 | -0.17692 |
| 3 | -4 | -0.12489 |
| 4 | -3 | -0.05812 |
| 5 | -2 | 0.06159 |
| 6 | -1 | 0.11237 |
| 7 | 0 | 0.27895 |
| 8 | 1 | 0.3036 |
| 9 | 2 | 0.26269 |
| 10 | 3 | 0.28215 |
| 11 | 4 | 0.26897 |
| 12 | 5 | 0.26934 |
| 13 | 6 | 0.26065 |

The cross-correlation results show the following patterns:

- For negative lags (where current stock prices are compared with future sentiment), the correlation weakens progressively. At a lag of -6 months, the correlation value is -0.26613, indicating a weak inverse relationship between stock prices and sentiment six months later.
- As the lag decreases, the correlation becomes less negative and eventually positive. At a lag of -1 month, the correlation increases to 0.11237.
- At zero lag (when both variables are considered in the same month), the correlation reaches 0.27895, indicating a moderate positive relationship between sentiment and stock prices.
- The strongest positive correlation occurs at a lag of +1 month, with a value of 0.3036. This suggests that sentiment has a weak positive correlation with stock prices in the following month.
- The correlation decreases slightly at lags of +2 months (0.26269) and +3 months (0.28215), before stabilizing around 0.26 at lags from +4 to +6 months.

The cross-correlation results indicate a weak positive correlation between Tesla's media sentiment and stock prices in the short term, particularly at a lag of +1 month. Correlations at other time lags are even weaker and do not provide substantial evidence of a strong relationship.

**Granger Causality Test Results for Tesla Media Sentiment and Stock Prices**

The Granger causality test was conducted to assess whether past media sentiment has predictive power for Tesla's future stock prices.

**Table 2:** *Granger causality test results assessing the predictive power of Tesla's media sentiment over stock prices*

| No | Time lags (in months) | P-value | F-statistical value |
|---|---|---|---|
| 1 | 1 | 0.81998 | 0.052198 |
| 2 | 2 | 0.641396 | 0.447253 |
| 3 | 3 | 0.154161 | 1.814482 |
| 4 | 4 | 0.088564 | 2.131913 |
| 5 | 5 | 0.189398 | 1.552058 |
| 6 | 6 | 0.142962 | 1.688090 |

The Granger causality test results indicate that, for all time lags, Tesla's media sentiment has little to no predictive power for Tesla's future stock prices. Specifically:

- At a lag of 1 month, the p-value is 0.81998 and the F-statistic is 0.052198, suggesting no significant relationship between sentiment and stock prices.
- At a lag of 2 months, the p-value is 0.641396 and the F-statistic is 0.447253, further indicating no significant predictive power.
- At a lag of 3 months, the p-value is 0.154161, and the F-statistic is 1.814482, which is not statistically significant.

- A lag of 4 months shows a slightly higher potential for a relationship, with a p-value of 0.088564 and an F-statistic of 2.131913, but this does not meet the conventional 5% significance threshold.
- For lags of 5 and 6 months, the p-values (0.189398 and 0.142962) and F-statistics (1.552058 and 1.688090) further confirm the lack of predictive power for sentiment.

The results suggest that media sentiment does not have strong or consistent predictive power for Tesla's stock prices. While there is some weak evidence of a potential delayed effect (especially at a 4-month lag), the relationships are not statistically significant enough to draw firm conclusions.

**Relationship Between Media Sentiment Regarding "Meta" and Company's Stock Prices**
**Media Sentiment and Meta Stock Prices: Time Series Analysis**

The initial examination of the relationship between Metas media sentiment and adjusted closing prices was conducted by analyzing two graphs.

**Figure 3**

*The monthly averages of sentiment scores for Meta-related media coverage from 2019 to October 2024*

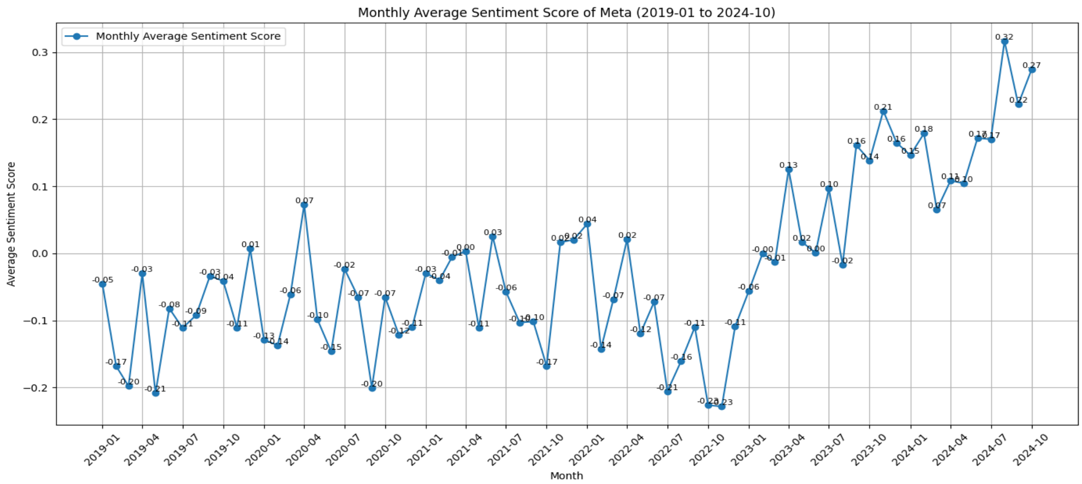
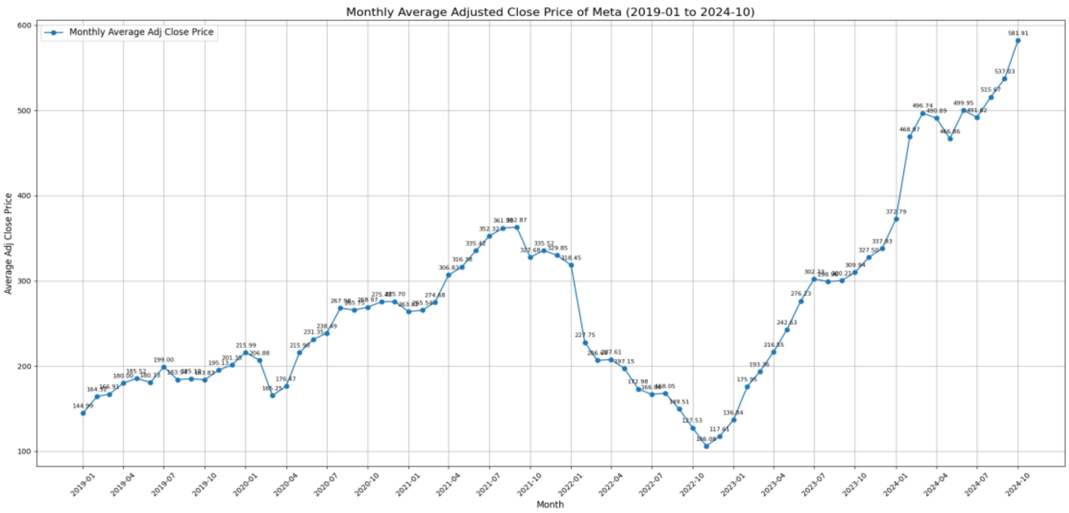



**Figure 4**

*The monthly averages of Meta's adjusted closing stock prices from* 2019 to October 2024



The analysis showed variability in monthly average sentiment scores throughout the period. In contrast, stock prices demonstrated clearer trends, with increases observed from 2019 to mid-2021, followed by a significant decline at the start of 2022 and recovery beginning in early 2023.

Periods of alignment between the two variables were identified, where both sentiment scores and stock prices moved in the same direction—either increasing or decreasing. However, such occurrences were less frequent compared to Tesla's case. In other periods, the variables moved in opposite directions. For instance, between early 2022 and early 2023, sentiment scores were largely negative, but stock prices showed a recovery trend.

These observations suggest a statistical relationship between sentiment scores and stock prices, warranting further analysis. Due to the non-linear nature of the observed relationship, cross-correlation and Granger causality analyses were used to examine these interactions in greater detail.

**Cross-Correlation Results for Meta Media Sentiment and Stock Prices**

The cross-correlation analysis evaluated the relationship between Meta's monthly sentiment scores and stock prices at varying time lags.

**Table 3:** *Cross-correlation values between Meta's media sentiment scores and the company's adjusted closing prices*

| No | Time lags (in months) | Correlation values |
|---|---|---|
| 1 | -6 | 0.28661 |
| 2 | -5 | 0.37115 |
| 3 | -4 | 0.45333 |
| 4 | -3 | 0.49859 |
| 5 | -2 | 0.57393 |
| 6 | -1 | 0.62808 |
| 7 | 0 | 0.72365 |
| 8 | 1 | 0.70140 |
| 9 | 2 | 0.67714 |
| 10 | 3 | 0.60854 |
| 11 | 4 | 0.59320 |
| 12 | 5 | 0.55159 |
| 13 | 6 | 0.50189 |

Key findings include:

- Negative Lags (Stock Prices Influencing Future Sentiment): Correlation values increase as the lag decreases, starting from 0.28661 at a lag of -6 months and reaching 0.62808 at -1 month. This indicates that current stock prices may moderately influence media sentiment in the following months.
- Direct Correlation (Lag of 0 Months): The highest correlation value (0.72365) was observed at lag 0, indicating the strongest relationship between sentiment and stock prices occurs within the same month.
- Positive Lags (Sentiment Influencing Future Stock Prices): At a lag of +1 month, the correlation was strong at 0.70140 but slightly weaker than the direct correlation. Correlation values decreased further with increasing positive lags, stabilizing between 0.55159 and 0.50189 for lags of +4 to +6 months.

The results demonstrate strong short-term correlations between sentiment scores and stock prices, particularly within the same month (lag 0) and in the following 1–2 months. Moderate correlations persist at longer lags.

**Granger Causality Analysis for Meta Media Sentiment and Stock Prices**

The Granger causality analysis was conducted to determine whether media sentiment scores could predict Meta's stock prices.

**Table 4:** *Granger causality test results assessing the predictive power of Meta's media sentiment over stock prices*

| No | Time lags (in months) | P value | F statistical value |
|---|---|---|---|
| 1 | 1 | 0.004630166 | 8.594116922 |
| 2 | 2 | 0.059407634 | 2.953726074 |
| 3 | 3 | 0.312826958 | 1.212948449 |
| 4 | 4 | 0.406054845 | 1.017605095 |
| 5 | 5 | 0.483301078 | 0.907217268 |
| 6 | 6 | 0.058736101 | 2.192667189 |

- Short-Term Predictive Power (Lags of 1–2 Months): At a lag of 1 month, the p-value (0.00463) and F-statistic (8.594117) indicate strong statistical significance, suggesting that sentiment scores effectively predict stock prices one month later. At a lag of 2 months, predictive power remains notable with a p-value of 0.059408.
- Mid-Term Predictive Power (Lags of 3–5 Months): For lags of 3–5 months, p-values exceed significance thresholds, ranging from 0.312827 to 0.483301, and F-statistics remain below meaningful levels, indicating no significant predictive power.
- Long-Term Predictive Power (Lag of 6 Months): At a lag of 6 months, the p-value (0.058736) and F-statistic (2.192667) indicate a marginal predictive relationship. However, the significance level is insufficient to establish a robust link.

The analysis shows that Meta's sentiment scores have strong predictive power for short-term stock price movements (1–2 months), but this diminishes over longer time frames.

**Further Examination of Time Lags: Insights from Cross-Correlation and Granger Causality Test**

Following the cross-correlation results and Granger causality test, a detailed examination was conducted for each month within the analyzed period (January 2019 to October 2024). This analysis aimed to practically assess how frequently the monthly average of sentiment scores and the monthly average of adjusted stock closing prices moved in the same direction at the specific time lags identified in the cross-correlation and Granger causality tests. By doing so, the study seeks to validate the observed relationships and gain deeper insights into the temporal dynamics of sentiment-driven stock price movements for Tesla and Meta.

For Tesla, the strongest negative correlation was identified at -6 months (-0.2661), the strongest positive correlations – in the same period (0 month) (0.27895), and +1 month (0.3036).

**Table 5:** *Further examination of cross-correlation and Granger causality test results for Tesla*

| Time lag (in months) | Cases moving in the same direction | Cases moving in the opposite direction |
|---|---|---|
| 0 | 24 | |
| 1 | 22 | |
| -6 | | 13 |
| *In total* | *46* | *13* |

For Meta, the strongest correlations were identified at 0 months (-0.72365), +1 month (0.70140), and +2 months (0.67714).

**Table 6:** *Further examination of cross-correlation and Granger causality test results for Meta*

| Time lag (in months) | Cases moving in the same direction |
|---|---|
| 0 | 15 |
| 1 | 19 |
| 2 | 40 |
| *In total* | *74* |

The results indicate significant correlations between selected time lags and the dynamics of sentiment and stock prices. For Tesla, the largest number of cases occurred at 0 and +1 month lags, while for Meta, the most significant intervals were +1 and +2 months. Furthermore, directional movement analysis reveals that after conducting a cross-correlation study and examining months in practical terms, and analyzing directional movements, sentiment and stock prices for Tesla are most strongly correlated within the same period. In contrast, for Meta, sentiment is most closely related to price changes after a two-month lag.

## 9. Discussions/Conclusions

Cross-correlation analysis examining the Tesla case revealed a weak but noticeable relationship between Tesla's stock prices and media sentiment, depending on the time lag. Negative time lags demonstrated a weak and often negative correlation between current stock prices and future sentiment scores, with the most significant negative correlation (-0.26613) observed at a -6-month lag. While this suggests a potential inverse relationship, the correlation is too weak to draw firm conclusions. As the negative lag decreases, the correlation weakens further and eventually fades away.

Positive time lags indicated a slightly stronger positive correlation between current sentiment and future stock prices. The highest positive correlation (0.3036) was observed at a +1-month lag, suggesting that current sentiment has a short-term impact on stock prices over the next month. Over a longer horizon (from +2 to +6 months), the correlations remain minimal and gradually diminish. Cross-correlation analysis revealed that changes in media sentiment about Tesla have the greatest impact on stock prices in the short term, with the market responding almost immediately to sentiment changes. However, the weak correlation values indicate that this impact is not substantial.

The Granger causality test was conducted to evaluate the predictive power of Tesla-related sentiment scores for future stock prices. The results showed that sentiment is not a reliable indicator for predicting future stock price movements. Even with a 1-month lag, where cross-correlation analysis indicated some influence of sentiment on stock prices, the predictive power was low. These findings suggest that sentiment has a limited impact on Tesla's stock price movements and is not suitable as a primary factor for predicting stock price dynamics.

Cross-correlation and Granger causality tests on the relationship between Meta's media sentiment and stock prices revealed a stronger positive relationship throughout the analyzed period, especially in the short term. Cross-correlation results indicated that current sentiment is most closely linked to stock closing prices in the same period (correlation 0.72365) and has a significant effect on prices observed after 1–2 months. It was also noted that current stock prices could influence future sentiment, particularly with a 1–2 month time lag.

Granger causality analysis demonstrated that media sentiment about Meta could be useful for predicting short-term stock price changes. The most significant predictive potential was observed at a 1-month lag (p-value = 0.0046), though the predictive strength diminished for longer time lags.

The analysis concluded that both Tesla and Meta's media sentiment are linked to their stock prices, though the strength and nature of this relationship vary by time frame. For Tesla, sentiment impact on stock prices is noticeable only in the same period or the following month, though the effect is not highly significant. Conversely, Meta's sentiment impact is stronger, most evident in the same period and in stock prices over the next 1–2 months. These findings align with previous studies, such as Zhang, Fuehres, and Gloor (2020), who demonstrated the predictive power of social media sentiment, particularly Twitter, for stock market indicators. These results suggest that the market reacts almost immediately to sentiment changes for both companies, though the intensity of reactions differs. Additionally, Tesla's current stock prices exhibit a certain inverse relationship with future sentiment, which becomes more significant over a longer horizon.

The Granger causality test revealed that media sentiment about Tesla is not useful for predicting future stock prices over any time frame. Meanwhile, sentiment about Meta may be valuable for predicting stock prices in the short term, particularly with a 1–2 month lag.

These findings indicate that both companies, particularly Meta, are sensitive to media sentiment, which drives market reactions and shapes investor expectations. For Meta, sentiment proves to be a valuable tool for predicting short-term stock price changes, while Tesla's market reactions appear more immediate. These results align with observations by Rishi (2022), who noted that behavioral biases often influence closing stock prices, leading to deviations from market efficiency. Rishi's comprehensive analysis suggests that such biases may exacerbate the impact of external factors like media sentiment, particularly when markets are influenced by emotional or psychological triggers. By contrasting these findings with traditional notions of market efficiency, as proposed by Fama (1970), this study underscores the dynamic interplay between rational market behavior . Tesla's rapid market responses may be influenced by the high-profile personality and active media presence of its CEO, whereas Meta's 1–2 month delays could reflect its reliance on long-term strategic narratives. However, these assumptions require further investigation to better understand such factors.

This study is not without limitations. While the use of monthly averages effectively identifies broader trends, it may obscure daily or weekly variations and does not account for external influences such as macroeconomic events. Future research could address these limitations by exploring additional variables, incorporating a wider range of companies, or utilizing intraday data to develop a more granular understanding of the interplay between media sentiment and stock price movements.

**Practical Implications of the Study**

1. Investor Strategies: Investors may use sentiment analysis as a supplementary tool for short-term trading strategies, particularly during periods of heightened media activity. For example, Meta's sentiment-driven short-term stock price changes provide actionable insights for traders.
2. Corporate Communication: Companies should monitor and respond to media sentiment promptly. For instance, Tesla and Meta could benefit from active management of public narratives to stabilize market perceptions and reduce volatility.
3. Risk Management: Financial institutions and asset managers can integrate sentiment analysis into risk assessment models, identifying periods of potential market overreaction to negative sentiment.

**REFERENCES**

1. CompaniesMarketCap. (2024). *Meta market capitalization and stock prices*. Retrieved November 22, 2024, from https://companiesmarketcap.com/meta-platforms/marketcap/
2. CompaniesMarketCap. (2024). *Tesla market capitalization and stock prices*. Retrieved November 22, 2024, from https://companiesmarketcap.com/tesla/marketcap/
3. Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417.

4. Hutto, C. J., & Gilbert, E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. In Proceedings of the Eighth International Conference on Weblogs and Social Media (ICWSM-14). Association for the Advancement of Artificial Intelligence (AAAI).
5. Granger, C. W. J. (1969)**.** Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, 37(3), 424–438.
6. Grigaitė, V. (2021). *Analysis of Relationship between Macroeconomic Indicators and Stock Market Sectors* (Master's Final Degree Project). Kaunas University of Technology, Faculty of Mathematics and Natural Sciences.
7. Loughran, T., & McDonald, B. (2011). When is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), 35–65.
8. Mohan, A., Vemuri, S., & Mandal, S. (2019)**.** Sentiment Analysis and Market Trends Prediction in Emerging Economies. *Journal of Economic Studies*, 46(6), 1153–1172.
9. Mohanty, A., & Roy, B. (2021). Cross-Correlation Analysis for Sentiment and Market Trends: A Case Study. *Journal of Market Analytics*, 15(2), 87–98.
10. Rishi, M. (2022). Market Efficiency and Behavioral Bias in Closing Stock Prices: A Comprehensive Analysis. *Financial Analysts Journal*, 78(4), 50–66.
11. Singh, A., Aggarwal, V., & Chauhan, G. (2022). Analyzing Sentiments on Social Media Platforms for Stock Market Predictions. *Journal of Financial Markets and Institutions*, 12(2), 203–220.
12. Xue, H. (2023)**.** Sentiment Analysis in Financial Markets: A Deep Learning Approach. *Applied Artificial Intelligence*, 37(2), 145–162.
13. Zhang, X., Fuehres, H., & Gloor, P. A. (2020). Predicting Stock Market Indicators Through Twitter: "I hope it is not as bad as I fear". *Procedia - Social and Behavioral Sciences*, 26, 55–62.