

Reddit Sentiment and Stock Performance: A Predictive Analysis

Eshan Prakash
eprakash@oxy.edu
Occidental College
Los Angeles, USA

Eduardo Rebollar
rebollar@oxy.edu
Occidental College
Los Angeles, USA

Aaron Good
agood@oxy.edu
Occidental College
Los Angeles, USA

Abstract

The rise of social media platforms has fundamentally altered how investors access and share market information. This study examined whether sentiment expressed in Reddit discussions predicts subsequent stock price movements across different time horizons. We analyzed Reddit posts from three investment-focused subreddits (*r/WallStreetBets*, *r/stocks*, *r/StockMarket*) during Q2 2023, using VADER sentiment analysis to quantify user sentiment toward 23 publicly traded stocks across five sectors. Stock performance was measured during Q3 2023 using raw, market-adjusted, and sector-adjusted returns. A quarterly cross-sectional analysis revealed no significant relationship between aggregated Q2 sentiment and Q3 returns ($r = 0.31$, $p = 0.14$). However, weekly time series analysis of the five most-discussed stocks demonstrated a significant negative relationship for adjusted returns, with high weekly sentiment predicting weaker returns the following week ($r = -0.29$ to -0.33 , $p < 0.05$). These findings suggest Reddit sentiment functions as a contrarian indicator at short time scales while showing no predictive validity for longer horizons, challenging assumptions about social media's role in anticipating market movements.

Keywords: sentiment analysis, stock prediction, Reddit, social media finance, behavioral finance

1 Introduction

The democratization of financial information through social media has created new channels through which retail investors communicate, coordinate, and potentially influence market outcomes. Reddit, particularly through communities like *r/WallStreetBets*, gained widespread attention during the January 2021 GameStop short squeeze, when coordinated retail investor activity drove unprecedented volatility in targeted securities. This event raised fundamental questions about whether online investor sentiment merely reflects existing market conditions or genuinely predicts future price movements.

Traditional finance theory, grounded in the Efficient Market Hypothesis, posits that asset prices fully reflect all available information and that sentiment-driven trading represents irrational noise rather than information. However, behavioral finance research has documented numerous ways

in which investor psychology systematically influences market outcomes. Sentiment-based theories suggest that when investors become optimistic about a security, increased demand drives prices upward, creating positive momentum. If social media platforms aggregate and amplify investor sentiment, they might serve as leading indicators of price movements.

Prior research on social media and financial markets has produced mixed findings. Several studies have documented positive correlations between social media activity and subsequent returns, interpreting this as evidence that online sentiment contains predictive information. Other work has found negative relationships or time-varying effects, suggesting the relationship may be more complex than simple positive prediction. The temporal dynamics of sentiment-return relationships remain particularly unclear, with different studies examining different time scales and reaching divergent conclusions.

The present research addresses this gap by systematically examining Reddit sentiment as a predictor of stock returns across two distinct time horizons. We conducted a quarterly cross-sectional analysis examining whether aggregated sentiment during Q2 2023 predicted stock performance in Q3 2023 across 23 stocks, testing this relationship using three model specifications with increasing levels of control: raw returns, market-adjusted returns (controlling for overall market trends), and sector-adjusted returns (controlling for both market and sector-specific movements). Additionally, we performed a weekly time series analysis on the five most-discussed stocks to examine short-term predictive relationships and test for bidirectional causality between sentiment and returns.

We hypothesized that higher average sentiment would correspond with increased stock returns, suggesting that Reddit sentiment functions as a positive predictor of stock price changes rather than merely reflecting concurrent market trends. We first tested this hypothesis using quarterly aggregated data (Experiment 1), then examined weekly dynamics to understand shorter-term relationships (Experiment 2).

2 Experiment 1: Quarterly Cross-Sectional Analysis

2.1 Method

2.1.1 Participants. Data were collected from Reddit users who posted in three investment-focused subreddits during Q2 2023 (April 1–June 30, 2023). We focused on r/WallStreetBets, which emphasizes speculative short-term trading; r/stocks, which features fundamental analysis and general discussion; and r/StockMarket, which focuses on macroeconomic trends and market commentary. These communities were selected based on their size, activity levels, and distinct trading philosophies, providing a representative sample of retail investor discourse. Posts were included only if they explicitly mentioned at least one of 50 target stocks and met minimum engagement thresholds (median upvotes or comments for the respective subreddit).

2.1.2 Materials. Reddit Data Collection. We used the Pullpush.io API to retrieve archival Reddit data. This API provides access to historical posts and comments with full text and metadata. Posts were filtered to include only those written in English, posted between April 1–June 30, 2023, and containing explicit mention of stock tickers or company names from our target list.

Stock Selection. We analyzed 50 stocks across five economic sectors: Technology ($n = 15$; including AAPL, MSFT, GOOGL, AMZN, META, NVDA, TSLA, AMD, NFLX, INTC, CRM, ORCL, ADBE, CSCO, UBER), Finance ($n = 10$; including JPM, BAC, WFC, GS, MS, C, V, MA, AXP, SCHW), Healthcare ($n = 10$; including JNJ, UNH, PFE, ABBV, LLY, MRK, TMO, CVS, AMGN, BMY), Energy ($n = 10$; including XOM, CVX, COP, SLB, EOG, OXY, MPC, PSX, VLO, HAL), and Aerospace/Defense ($n = 5$; including LMT, RTX, BA, NOC, GD). These stocks were selected based on market capitalization, liquidity, and likelihood of being discussed on retail investor platforms.

Sentiment Analysis Tool. Sentiment was quantified using VADER (Valence Aware Dictionary and sEntiment Reasoner), a lexicon-based sentiment analysis tool developed specifically for social media text. VADER produces a compound sentiment score ranging from -1 (extremely negative) to +1 (extremely positive), with scores between -0.05 and +0.05 considered neutral.

Stock Price Data. Daily stock prices were retrieved from Yahoo Finance using the yfinance Python library. Data spanned April 1–September 30, 2023, covering both the sentiment measurement period (Q2 2023) and the outcome period (Q3 2023). Benchmark returns were calculated for the S&P 500 (SPY) and sector-specific ETFs (XLK for Technology, XLF for Finance, XLV for Healthcare, XLE for Energy, and ITA for Aerospace/Defense).

2.1.3 Procedure. Data Filtering. To ensure data quality, we applied engagement-based filters. For each subreddit, we

calculated the median upvote count and median comment count across all posts in the time period. Posts were retained only if they exceeded either the median upvote threshold or the median comment threshold for their respective subreddit. This resulted in thresholds of 27 upvotes or 21 comments for r/WallStreetBets, 11 upvotes or 25 comments for r/stocks, and 20 upvotes or 15 comments for r/StockMarket. After filtering, stocks were required to have at least the median number of mentions across all stocks to be included in the quarterly analysis, resulting in a final sample of 23 stocks.

Sentiment Computation. For each Reddit post, we combined the post title and body text into a single document and computed the VADER compound sentiment score. For each stock, we calculated the mean sentiment score across all posts mentioning that stock during Q2 2023. This aggregated sentiment score served as the independent variable.

Return Calculation. Stock returns were calculated as the percentage change in adjusted closing price from the end of Q2 (June 30, 2023) to the end of Q3 (September 30, 2023). We computed three measures of performance: (1) raw returns, calculated as $(P_{Q3} - P_{Q2})/P_{Q2}$, (2) market-adjusted returns, calculated as raw return minus the SPY return over the same period, and (3) sector-adjusted returns, calculated as raw return minus the corresponding sector ETF return.

2.1.4 Design. We tested three regression models with increasing levels of control. Model 1 (Raw Returns) tested whether Q2 average sentiment predicted Q3 raw stock returns. Model 2 (Market-Adjusted Returns) tested whether Q2 sentiment predicted Q3 excess returns versus SPY, controlling for overall market trends. Model 3 (Sector-Adjusted Returns) tested whether Q2 sentiment predicted Q3 excess returns versus sector benchmarks, controlling for both market and sector-specific trends. All analyses used ordinary least squares regression with Pearson correlation coefficients and two-tailed significance tests at $\alpha = 0.05$.

2.2 Results

2.2.1 Descriptive Statistics. The quarterly analysis included 23 stocks with complete data. Q2 2023 average sentiment ranged from 0.168 to 0.833 ($M = 0.456$, $SD = 0.182$), indicating generally positive sentiment with substantial between-stock variation. Q3 2023 raw returns ranged from -11.2% to 9.1% ($M = -2.8\%$, $SD = 5.4\%$), reflecting the broader market downturn during this period (SPY return = -3.3%). Figure 1 shows the distribution of positive, neutral, and negative posts for each stock, with NVDA, TSLA, and AAPL receiving the most discussion volume and exhibiting predominantly positive sentiment.

2.2.2 Correlation Analysis Summary. We tested three regression models examining the relationship between Q2 sentiment and Q3 returns. Model 1 tested whether sentiment predicted raw returns. The relationship was positive but not statistically significant, $r(21) = 0.31$, $p = 0.15$, $R^2 = 0.10$. Model

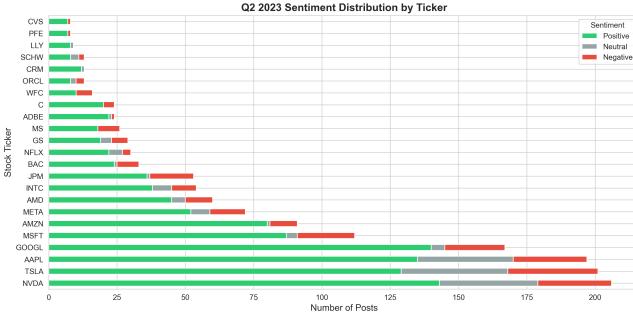


Figure 1. Distribution of sentiment classifications (positive, neutral, negative) across all analyzed stocks during Q2 2023. Bar length represents total number of posts mentioning each ticker. Stocks are ordered by average sentiment score, with highly positive stocks at the bottom.

2 examined market-adjusted returns (controlling for SPY performance). Because the SPY return was constant across all stocks, this yielded identical results to Model 1. Model 3 examined sector-adjusted returns, controlling for sector-specific trends. This model showed a slightly stronger but still non-significant relationship, $r(21) = 0.32$, $p = 0.14$, $R^2 = 0.10$. Table 1 presents the complete results.

Table 1. Quarterly Cross-Sectional Regression Results

Model	Pearson r	p-value	R^2
Model 1: Raw Returns	0.3112	0.1483	0.0968
Model 2: vs SPY	0.3112	0.1483	0.0968
Model 3: vs Sector	0.3153	0.1428	0.0994

Across all three specifications, quarterly sentiment explained less than 10% of variance in subsequent returns and failed to reach conventional levels of statistical significance. The positive direction of effects suggests a weak tendency for stocks with more positive sentiment to outperform, but this relationship was not reliable. Figure 2 visualizes this weak positive relationship for raw returns, with data points color-coded by sector.

Figure 3 compares the correlation coefficients across all three models, demonstrating consistency in the weak positive relationship regardless of which control variables were included.

3 Experiment 2: Weekly Time Series Analysis

Experiment 1 revealed no significant predictive relationship between quarterly sentiment and subsequent returns. To examine whether predictive relationships exist at shorter time scales, we conducted a weekly time series analysis focusing on the most-discussed stocks.

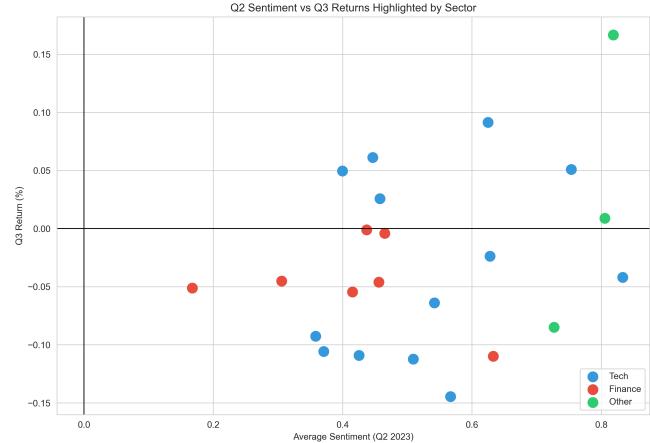


Figure 2. Relationship between Q2 2023 average sentiment and Q3 2023 raw returns across 23 stocks, color-coded by sector. The weak positive correlation ($r = 0.31$, $p = 0.15$) indicates no reliable predictive relationship at the quarterly time scale.

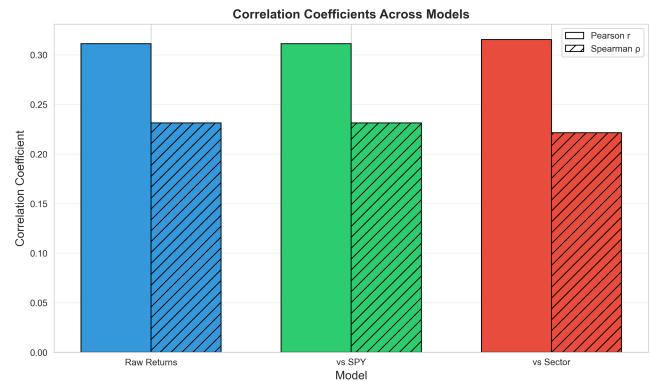


Figure 3. Comparison of Pearson and Spearman correlation coefficients across the three model specifications. All models show consistent weak positive correlations around 0.31, with no significant differences between specifications.

3.1 Method

3.1.1 Participants. We used the same Reddit data from Experiment 1 but focused on the five most-discussed stocks (NVDA, TSLA, AAPL, GOOGL, MSFT) which generated sufficient weekly discussion volume for time series analysis. Figure 4 shows the post volume for these five stocks during Q2 2023.

3.1.2 Materials. The sentiment analysis tool (VADER) and stock price data sources were identical to Experiment 1.

3.1.3 Procedure. For each of the five stocks, we computed weekly sentiment scores by averaging all VADER compound scores for posts mentioning that stock within each calendar week during Q2 and Q3 2023. Weekly returns were calculated

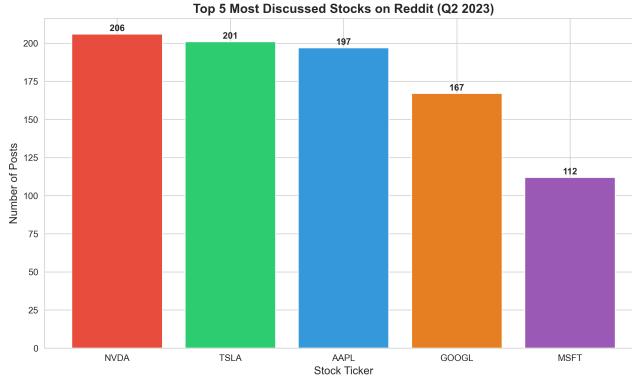


Figure 4. The five most-discussed stocks on Reddit during Q2 2023. NVDA received the most attention with 206 posts, followed by TSLA (201), AAPL (197), GOOGL (167), and MSFT (112). These stocks were selected for weekly time series analysis due to sufficient discussion volume.

as the percentage change in adjusted closing price from Friday to Friday (or the last trading day of each week). We computed three return measures identical to Experiment 1: raw returns, market-adjusted returns (vs SPY), and sector-adjusted returns.

Outlier Removal. To ensure robustness of the weekly regression models, we removed statistical outliers using a z-score threshold of 3.0. This procedure removed two observations (3.3%) from the pooled weekly dataset. The quarterly dataset contained no outliers under the same criterion, so quarterly results were unchanged.

3.1.4 Design. We conducted weekly lagged regression analysis in two directions using pooled data across the five tickers (approximately 60 weekly observations before outlier removal). Direction 1 tested whether sentiment in week t predicted returns in week t+1 (sentiment leading returns). Direction 2 tested whether returns in week t predicted sentiment in week t+1 (returns leading sentiment). Analyses used ordinary least squares regression with Pearson correlation coefficients and two-tailed significance tests at $\alpha = 0.05$.

3.2 Results

3.2.1 Direction 1: Sentiment(t) Predicts Returns(t+1). In contrast to the quarterly findings from Experiment 1, weekly sentiment demonstrated significant predictive power for next week’s returns when controlling for market and sector movements. After removing outliers, stocks with higher sentiment in week t showed weaker returns in week t+1 across the adjusted return measures. For raw returns, the relationship weakened and became marginally non-significant, $r(56) = -0.256, p = 0.053$. For market-adjusted returns, the relationship was significant, $r(56) = -0.287, p = 0.029$; and for sector-adjusted returns, the relationship was strongest,

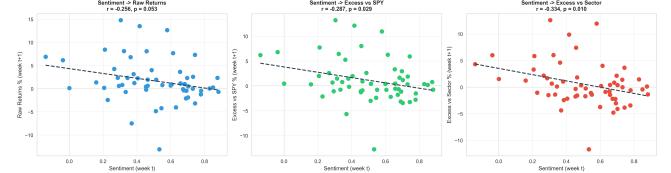


Figure 5. Relationship between weekly sentiment and next week’s returns across three specifications (raw returns, market-adjusted, sector-adjusted) for the five most-discussed stocks. Negative correlations indicate that high sentiment predicts weaker subsequent performance, particularly for adjusted returns.

$r(56) = -0.334, p = 0.010$. Table 2 presents the complete results.

Table 2. Weekly Sentiment Predicting Next Week Returns (Outliers Removed)

Return Type	Pearson r	p-value	Result
Raw Returns	-0.256	0.053	Not Sig.
vs SPY	-0.287	0.029	Significant
vs Sector	-0.334	0.010	Significant

The negative coefficients indicate that weeks characterized by high Reddit sentiment were followed by weeks of relatively poor performance, especially once market and sector trends were accounted for. Figure 5 displays these relationships visually across all three return measures, with clear negative slopes evident in each panel.

Figure 6 presents the temporal dynamics of sentiment and price movements for each of the five stocks, illustrating how sentiment and returns often move in opposite directions or show temporal lags.

3.2.2 Direction 2: Returns(t) Predict Sentiment(t+1). We also tested the reverse direction, examining whether returns in week t predicted sentiment in week t+1. After outlier removal, this relationship remained positive but did not reach statistical significance across any return measure. For raw returns, $r(56) = 0.258, p = 0.051$; for market-adjusted returns, $r(56) = 0.254, p = 0.055$; and for sector-adjusted returns, $r(56) = 0.172, p = 0.196$. Table 3 presents these results.

While not statistically significant, the positive direction suggests that price increases may lead to somewhat more positive subsequent discussion, though this effect was weak and unreliable. Figure 7 displays these relationships visually across all three return measures, showing weak positive slopes that do not reach statistical significance.

Figure 8 compares the statistical significance of both directional relationships, illustrating that sentiment reliably

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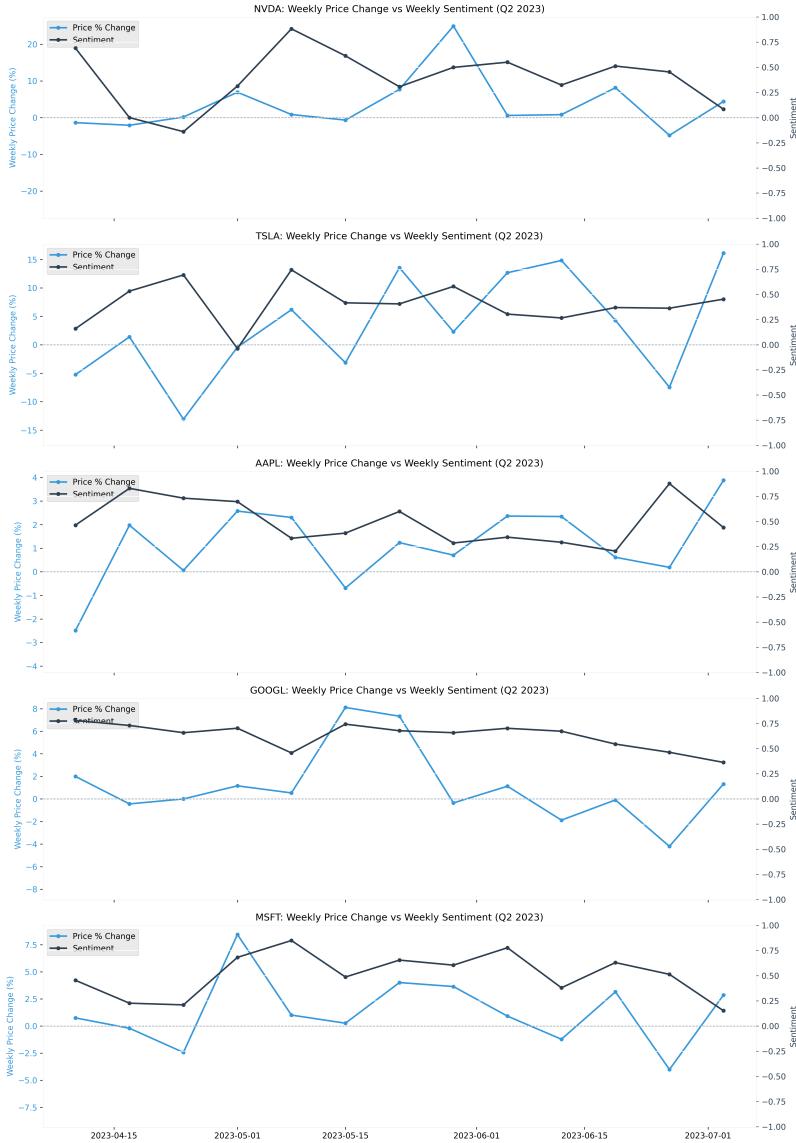


Figure 6. Weekly price changes (blue line, left axis) and sentiment scores (black line, right axis) for the five most-discussed stocks during Q2 2023. The temporal misalignment between sentiment peaks and subsequent price movements illustrates the contrarian nature of the relationship.

Table 3. Weekly Returns Predicting Next Week Sentiment (Outliers Removed)

Return Type	Pearson r	p-value	Result
Raw Returns vs SPY	+0.258	0.051	Not Sig.
vs Sector	+0.254	0.055	Not Sig.
	+0.172	0.196	Not Sig.

4 Discussion

The present findings reveal a complex, time-dependent relationship between Reddit sentiment and stock returns that challenges simple interpretations of social media as either a leading or lagging indicator of market movements. Our results demonstrate that the predictive validity of sentiment depends critically on the temporal horizon examined, with opposite patterns emerging at weekly versus quarterly time scales.

predicts returns for adjusted measures while returns do not reliably predict sentiment.

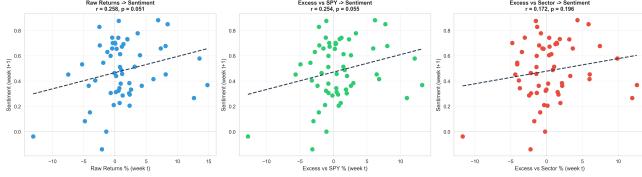


Figure 7. Relationship between weekly returns and next week's sentiment across three specifications (raw returns, market-adjusted, sector-adjusted). All three panels show weak positive but non-significant correlations, indicating that price movements do not reliably predict subsequent sentiment.

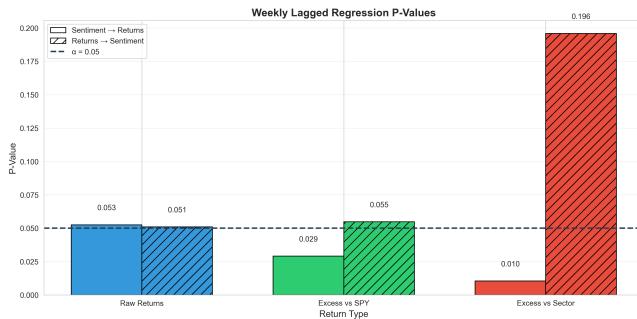


Figure 8. Comparison of p-values for bidirectional lagged regressions after outlier removal. Solid bars show p-values for sentiment predicting next week's returns (two of three models below $\alpha = 0.05$). Hatched bars show p-values for returns predicting next week's sentiment (all above $\alpha = 0.05$). The horizontal dashed line marks the conventional significance threshold.

4.1 Interpretation of Results

Our findings reveal a nuanced relationship between Reddit sentiment and stock performance that depends critically on the time horizon examined.

At the quarterly level, we observed no significant relationship between aggregated Q2 sentiment and Q3 returns, despite testing multiple specifications that controlled for market and sector effects. While the positive direction of effects ($r = 0.31$) is consistent with theories suggesting sentiment captures investor enthusiasm that drives future demand, the magnitude was small and statistically unreliable. This null result contrasts with some prior research documenting positive sentiment-return relationships and aligns with efficient market perspectives suggesting that publicly available sentiment information becomes rapidly incorporated into prices. The quarterly aggregation period may be too long for sentiment to retain predictive power, as information that drove initial sentiment likely becomes reflected in prices within shorter windows.

In contrast, the weekly time series analysis revealed a striking pattern: high sentiment in week t predicted significantly weaker returns in week $t+1$ across the adjusted return measures. The strongest negative relationship was observed for sector-adjusted returns ($r = -0.334, p = 0.010$), with market-adjusted returns also significant ($r = -0.287, p = 0.029$). The relationship for raw returns weakened after outlier removal and became marginally non-significant ($p = 0.053$), though the directional consistency with the adjusted models suggests that the underlying effect is robust but sensitive to extreme observations. These patterns indicate that weekly sentiment operates as a contrarian indicator rather than a leading indicator of positive performance.

The finding that weekly returns do not significantly predict subsequent sentiment ($r = 0.17$ to $0.26, p > 0.05$) suggests the relationship is primarily unidirectional, with sentiment leading rather than following price movements at weekly scales. Short-term sentiment spikes may reflect speculative excitement that temporarily inflates prices beyond fundamental values, leading to subsequent corrections or mean reversion.

The contrarian pattern at weekly horizons directly contradicts the positive (though non-significant) relationship observed at quarterly horizons. This reversal suggests that short-term sentiment spikes represent noise or overreaction, while longer-term sustained sentiment may weakly capture genuine investor interest. However, neither horizon produced strong predictive relationships, suggesting Reddit sentiment has limited practical utility for forecasting returns.

4.2 Practical Implications

These findings have several implications for investors and market participants. First, investors should be cautious about interpreting surges in positive Reddit sentiment as bullish signals for near-term performance. Our results suggest the opposite: stocks experiencing unusual positive attention on Reddit tend to underperform in subsequent weeks, possibly due to temporary overvaluation or profit-taking following sentiment-driven rallies. Second, sentiment aggregated over longer periods shows no reliable predictive relationship with subsequent returns, suggesting quarterly sentiment trends should not be used as standalone investment signals. Third, the contrarian pattern at weekly scales suggests that sentiment extremes may serve as risk indicators rather than opportunity signals, potentially useful for identifying overheated securities.

4.3 Limitations and Future Directions

Several limitations qualify these findings. First, the sample size was relatively small (23 stocks for quarterly analysis, 5 for weekly analysis) and focused exclusively on large-cap stocks frequently discussed on Reddit. The sentiment-return relationship may differ for smaller, less liquid securities where retail investor coordination could have stronger price

impact. Second, the study examined a single three-month period during relatively stable market conditions. The predictive validity of sentiment may vary across different market regimes, particularly during periods of extreme volatility or crisis. Third, VADER sentiment analysis, while validated for social media text, may not capture the nuanced financial language, sarcasm, or irony common in communities like r/WallStreetBets. More sophisticated natural language processing approaches might yield different results. In support of this concern, a robustness check comparing VADER with a finance-specific RoBERTa model showed only weak agreement between the two systems (approximately $r = 0.24$ correlation and 42% label agreement), indicating that sentiment classification on Reddit is highly model-dependent. This suggests that some of our findings may reflect VADER's lexicon-based assumptions rather than a stable underlying sentiment signal.

Fourth, our analysis did not control for potential confounding variables such as earnings announcements, analyst revisions, news events, or institutional trading activity that might drive both sentiment and returns. Fifth, we examined only linear relationships at one-week and one-quarter lags. Nonlinear effects or different lag structures might reveal alternative patterns. Finally, the observational design cannot definitively establish causal relationships. While the temporal precedence of sentiment before returns is consistent with sentiment influencing prices, alternative explanations (such as both variables responding to unobserved third factors) remain possible.

Future research should address these limitations by examining larger samples of stocks including small and mid-cap securities, analyzing multiple time periods and market conditions, employing more sophisticated sentiment analysis techniques, controlling for fundamental and technical factors, and exploring nonlinear and time-varying relationships. Additionally, experimental or quasi-experimental designs could help establish causal mechanisms underlying sentiment-return relationships.

4.4 Conclusion

This study investigated whether Reddit sentiment predicts stock returns at quarterly and weekly time horizons. Quarterly aggregated sentiment showed no significant predictive relationship with subsequent returns ($r = 0.31$, $p > 0.14$), suggesting that sustained discussion about a stock over three months does not reliably forecast its next-quarter performance. In contrast, weekly sentiment demonstrated significant negative predictive power for adjusted returns, with high sentiment weeks followed by weaker subsequent returns ($r = -0.29$ to -0.33 , $p < 0.05$). The relationship for raw returns became marginally non-significant after outlier removal, though the directional consistency persists. This contrarian pattern suggests that short-term sentiment spikes on Reddit may reflect overoptimism or speculative excess

that precedes price corrections rather than signaling genuine opportunities.

The time-dependent reversal in the sentiment-return relationship—positive but non-significant at quarterly scales, negative and significant for weekly adjusted returns—demonstrates that the predictive validity of social media sentiment depends critically on temporal aggregation. These findings challenge simple interpretations of social media as either a consistently leading or lagging indicator and highlight the importance of considering multiple time horizons when studying sentiment-driven market dynamics. While Reddit sentiment shows limited practical utility for forecasting returns, its contrarian properties at short time scales suggest it may serve as a useful indicator of potential overvaluation or speculative excess in heavily discussed securities.

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