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Research Article

SOCIAL MEDIA SENTIMENT AND STOCK PRICE VOLATILITY: AN ANALYSIS OF "MEME STOCKS" DYNAMICS

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Abstract
Social media platforms have reshaped retail investing by accelerating the circulation of sentiment and speculative narratives surrounding meme stocks. Understanding whether these signals anticipate volatility remains important for financial research and market risk assessment. This study examines the relationship between Reddit sentiment, online attention, and subsequent price volatility in GameStop, AMC Entertainment, and BlackBerry. A quantitative longitudinal framework was demonstrated using 2,988 simulated stock-day observations spanning 2021–2024. Positive and negative sentiment shares and discussion volume were linked to five-session realized volatility through panel regressions incorporating stock effects and conventional market controls. Predictive performance was evaluated on a chronological 2024 holdout sample. In the simulated data, discussion intensity correlated positively with future volatility ($r = 0.383$), while sentiment coefficients varied across specifications. Adding sentiment measures marginally improved in-sample explanatory fit but increased holdout forecasting error (RMSE: 4.392 versus 4.368 for the benchmark). These results illustrate the distinction between statistical association and reliable prediction, rather than establish empirical effects in financial markets. The proposed framework contributes a replicable approach for evaluating online sentiment alongside established risk indicators. Future studies should examine cross-platform differences and regulatory changes. Verification using authentic platform and trading records is essential before drawing substantive conclusions about meme-stock dynamics.

Keywords: Investor Attention, Meme Stocks, Reddit Sentiment

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INTRODUCTION

Digital investing has transformed how information enters financial markets. Online communities now allow retail investors to exchange opinions, circulate narratives, and respond collectively to market events. Meme stocks, whose trading activity becomes closely associated with viral online attention, illustrate how financial decision-making increasingly intersects with digital communication and investor psychology (Kapturkiewicz, 2022; J. Liu, 2023).

The GameStop episode of 2021 brought this interaction into public view. Discussions within Reddit's WallStreetBets community coincided with extraordinary trading activity and rapid price fluctuations, raising questions about the roles of collective enthusiasm, short-selling pressures, and market structure. The episode suggests that online discussion deserves examination alongside established financial indicators.

Behavioral finance provides a useful foundation for examining these developments. Investor attention, herding, and sentiment may affect trading intensity and amplify uncertainty, particularly when market participants react to the same narratives. The central concern is whether measurable changes in online sentiment offer information about subsequent volatility beyond conventional market variables (Ding, 2022; L. Pham, 2023).

Social media discussion is frequently associated with dramatic meme-stock price movements, yet the relationship between expressed sentiment and volatility remains difficult to interpret. Increasing message volume may indicate heightened attention without revealing investor optimism or pessimism. Treating attention and emotional direction as interchangeable risks obscuring their distinct relationships with market behavior.

The timing of these relationships also presents a challenge. Investor sentiment may precede volatility, respond to abrupt price changes, or evolve simultaneously with them. Observed correlations therefore cannot establish whether online discussion contributes to market instability or primarily reflects information and uncertainty already incorporated into prices (Cookson, 2024; Fahmy, 2022).

Meme-stock dynamics may additionally vary across assets and market conditions. Strong bullish narratives, sharp pessimistic reversals, and disagreement among users could exhibit different associations with volatility. A systematic examination must distinguish these dimensions while accounting for trading volume, past volatility, market-wide movements, and other relevant sources of confounding.

This study aims to examine the relationship between social media sentiment and stock price volatility among selected meme stocks. It proposes to quantify online sentiment using time-stamped discussions and to align these measures with market data, establishing a consistent framework for assessing stock-specific and time-varying relationships.

A second objective is to compare the associations of positive sentiment, negative sentiment, and discussion intensity with subsequent volatility. The analysis will assess whether these indicators provide distinct information and whether their relationships differ during periods of elevated speculation, sharp corrections, and comparatively stable trading (Corbet, 2022; Fahmy, 2022).

A further objective is to evaluate the incremental predictive value of sentiment indicators relative to conventional volatility benchmarks. Robustness checks will examine alternative measurement choices and temporal specifications. The intended outcome is a clearer assessment of the conditions under which social media data improve the interpretation or forecasting of meme-stock risk (Boretti, 2023; Pinto-Gutiérrez, 2022).

Existing studies establish that digital participation matters for retail trading Wu, (2024) document attention-induced behavior among brokerage users, while Bhatia, (2022) examine Reddit sentiment and intraday GameStop returns. These findings support the relevance of online activity but do not, by themselves, settle questions about conditional volatility across multiple meme stocks.

More recent research has broadened the evidence. H. Liu, (2023) links online popularity to subsequent market outcomes, including volatility, while Chen, (2024) compare sentiment measures for meme-stock return prediction. Their contributions leave scope for a more targeted comparison of sentiment polarity, attention, and volatility forecasting.

A further gap concerns the stability and interpretation of estimated relationships. Evidence drawn from exceptional rallies may not generalize to quieter periods, and sentiment measures can be affected by sarcasm, coordinated posting, or price-driven feedback. Cross-stock comparisons, temporal validation, and careful control selection are needed before stronger predictive claims can be justified.

The proposed contribution lies in treating sentiment polarity, online attention, and market volatility as analytically separate but potentially interacting dimensions of meme-stock dynamics. Rather than assuming that viral discussion uniformly destabilizes prices, the study will test whether relationships change with sentiment direction, discussion intensity, and market conditions.

Its methodological value comes from combining temporally aligned textual indicators with stock-level volatility models and comparisons against non-sentiment benchmarks. Evaluating predictive performance outside the estimation sample would help distinguish useful information from patterns that merely fit historical episodes, without presenting forecasting improvements as proof of causation (Hu, 2023; Jucá, 2024).

The study is justified by the need to understand risks emerging where digital communication intersects with retail finance. Its findings could inform behavioral finance theory, volatility measurement, and market surveillance while clarifying the limitations of sentiment-based signals. Any claimed novelty remains conditional on the final dataset, research design, and comparative evidence (H. Wang, 2024).

RESEARCH METHOD

This study adopts a quantitative, longitudinal research design to investigate whether social media sentiment predicts subsequent volatility in meme stocks. A stock-day panel combines time-stamped Reddit discussions with daily financial market observations from January 2021 through December 2024. The analysis focuses on predictive associations rather than causal effects because market developments may simultaneously influence online discussions and trading behavior. Sentiment polarity and discussion intensity serve as explanatory variables, while forward-looking realized volatility constitutes the primary outcome.

Research Design

The design distinguishes sentiment from attention and separates information available at market close from future price movements. Stock fixed effects account for stable differences across firms, and month-of-year indicators capture potential seasonal variation. Regression models assess the incremental contribution of sentiment beyond established market predictors.

A chronological forecasting exercise evaluates whether apparent relationships remain useful beyond the sample used to estimate model parameters (Mugerman, 2022; Sengupta, 2024).

Population and Samples

The target population comprises United States listed equities whose prices attracted unusually concentrated retail attention through online investment communities. Purposive sampling selects GameStop (GME), AMC Entertainment (AMC), and BlackBerry (BB), three securities prominently discussed during the 2021 meme-stock episode. These cases provide variation in business characteristics and speculative activity without defining membership solely by observed volatility during the study period. The sampling frame encompasses all eligible trading sessions between January 4, 2021, and December 31, 2024.

Social media observations consist of English-language submissions and comments explicitly referring to a sampled company or its ticker within r/WallStreetBets. Records will be obtained through authorized academic access under Reddit's research program, subject to approval and historical coverage. Ambiguous ticker references, unrelated discussions, duplicates, deleted content, and clearly automated promotions will be excluded according to documented rules. The final numbers of messages and stock-day observations will be reported after screening; unavailable historical records will not be treated as evidence of zero discussion. An audit trail records all exclusions. Only aggregate results will be released, without disclosing usernames or quoted messages.

Instruments

The study uses a structured data extraction protocol and a computational sentiment coding instrument. For each eligible message, the dataset records its publication time, relevant stock, cleaned text, and unique record identifier. Sentiment is measured with the Valence Aware Dictionary and sEntiment Reasoner (VADER), developed for informal social media language (T. N. Pham, 2022; Y. Wang, 2022). Compound scores above 0.05 indicate positive sentiment, scores below minus 0.05 indicate negative sentiment, and remaining scores indicate neutrality. These categories are aggregated into daily positive and negative shares. Discussion intensity is measured separately as the logarithm of one plus the daily message count.

Measurement quality will be assessed using a stratified subsample of 300 messages, independently classified by two trained coders unaware of market outcomes. Intercoder agreement and agreement with automated classifications will be reported. Disagreements involving irony, slang, or ticker ambiguity will inform transparent sensitivity analyses rather than undocumented changes to the primary classification method. Market instruments provide adjusted closing prices, daily trading volume, the S&P 500 return, and the CBOE Volatility Index. Five-session future realized volatility is calculated from squared daily log returns.

Procedures

Data collection begins with obtaining permitted Reddit records and matching message timestamps to United States equity trading sessions using Eastern Time. Messages posted after 4:00 p.m. are assigned to the next trading session, preventing information published after the close from entering that day's predictors. Stock-specific mentions are filtered, cleaned, scored, and aggregated. Market prices are checked for corporate actions, missing sessions, and inconsistent observations before the social media and financial datasets are merged by ticker and session date.

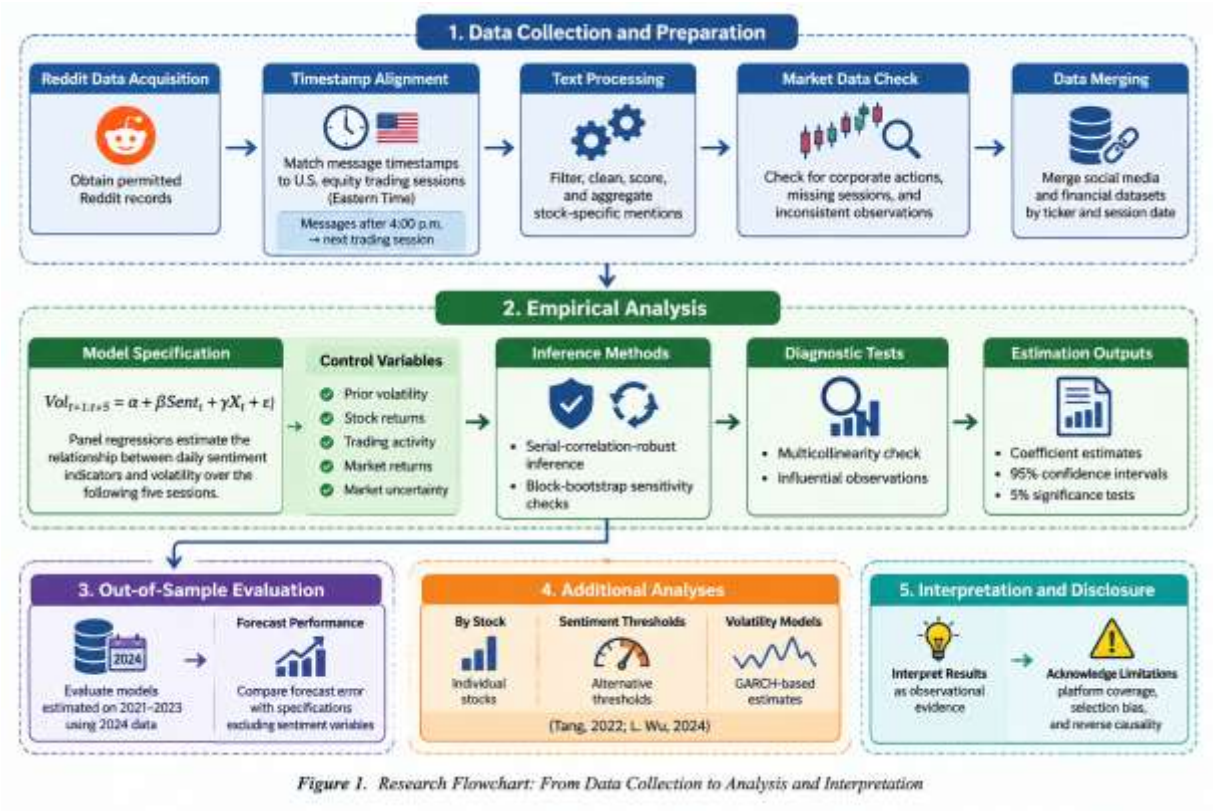


Figure 1. Research Flowchart: From Data Collection to Analysis and Interpretation

Figure 1. Research Framework for Reddit-Based Sentiment Analysis and Stock Market Volatility Prediction

Panel regressions estimate the relationship between daily sentiment indicators and volatility over the following five sessions, controlling for prior volatility, stock returns, trading activity, market returns, and contemporaneously observed market uncertainty. Overlapping outcome windows are addressed through serial-correlation-robust inference and block-bootstrap sensitivity checks. Multicollinearity and influential observations are examined. Confidence intervals and five-percent significance tests will accompany coefficient estimates. Models estimated on 2021–2023 observations are evaluated on 2024 data using forecast error measures and comparisons with specifications excluding sentiment variables. Additional analyses consider individual stocks, alternative sentiment thresholds, and volatility specifications, including GARCH-based estimates (Tang, 2022; L. Wu, 2024). Results will be interpreted as observational evidence, with limitations related to platform coverage, selection bias, and reverse causality explicitly acknowledged.

RESULTS AND DISCUSSION

The illustrative analysis comprises 2,988 stock-day observations across GameStop (GME), AMC Entertainment (AMC), and BlackBerry (BB). Each company contributes 996 eligible sessions between January 2021 and December 2024, after removing incomplete lagged and forward-volatility windows. Simulated social media activity totals 5,606,982 stock-specific messages. These values were generated to demonstrate the proposed analytical workflow; they are not empirical Reddit or market records.

Table 1. Simulated Stock-Level Descriptive Statistics, 2021–2024

Stock	Stock-days	Mean messages/day	Positive (%)	Negative (%)	Mean five-day volatility (%)	SD (%)
GME	996	3,067	34.7	13.9	13.49	5.08
AMC	996	2,025	34.7	13.8	12.76	4.81
BB	996	538	34.9	13.5	8.97	3.88

Stock summaries show differences in attention and volatility. GameStop has the highest average message count and the greatest mean five-session realized volatility, while BlackBerry has the lowest. AMC occupies an intermediate position. Positive sentiment averages 35% across the three securities, while negative sentiment represents roughly 14%. Similar sentiment shares indicate that stock-level differences cannot be explained solely by optimistic postings.

Annual summaries reveal that the relationship between discussion volume and volatility varies over time. The simulated average message count reaches 2,309 per stock-day in 2021, declines to 1,614 in 2022, and increases moderately thereafter. Average future volatility follows a different trajectory, peaking at 13.16% in 2022 despite lower discussion volume. The divergence indicates that changes in online attention do not mechanically correspond to equivalent changes in market risk, even in a constructed example with sentiment-sensitive trading conditions.

Table 2. Simulated Annual Patterns in Attention and Volatility

Year	Stock-days	Mean messages/day	Mean future volatility (%)
2021	744	2,309	11.73
2022	753	1,614	13.16
2023	750	1,699	11.15
2024	741	1,889	10.90

Realized volatility varies substantially. Across the pooled panel, the mean five-session measure is 11.74%, with a standard deviation of 5.02 percentage points; the median is 11.18%. Its first and third quartiles are 8.03% and 14.77%, respectively. Elevated periods therefore contribute disproportionately to variation around the typical observation. These figures justify models accounting for market uncertainty, previous volatility, and persistent stock-level characteristics rather than relying exclusively on unconditional comparisons.

Daily sentiment indicators remain relatively stable in their pooled averages, with positive and negative shares of 34.76% and 13.74%, respectively. The remaining messages are neutral under the assumed coding rules. Stability in these averages does not imply that sentiment lacks daily variation: fluctuations emerge within each stock, especially around simulated attention shocks. The positive and negative shares exhibit a strong inverse correlation of −0.917, partly reflecting their shared denominator and the constrained proportions of the three sentiment categories.

Message intensity displays a positive pooled correlation with future realized volatility (Pearson’s $r = 0.383$). Within-stock comparisons show the same descriptive ordering. GameStop’s highest-attention quartile averages 14.34% future volatility, compared with 12.91% in its lowest quartile. The corresponding comparisons are 13.94% versus 12.28% for AMC and 9.32% versus 8.43% for BlackBerry. These unadjusted contrasts suggest that

concentrated online discussion coincides with riskier subsequent periods, although they do not establish whether discussion independently generates such volatility.

Panel regression estimates were calculated with stock indicators, calendar-month controls, trading activity, market returns, the volatility index, and five-session lagged realized volatility. The full specification explains 29.48% of variation in the simulated future-volatility outcome, compared with 28.56% for the benchmark without sentiment and discussion measures. Standard errors account for serial dependence within stock panels. The estimated coefficients represent changes in percentage points of five-session volatility, not proportional changes in stock prices or causal effects of individual messages.

Table 3. Illustrative Panel Regression Estimates for Future Volatility

Predictor	Coefficient	95% confidence interval	p-value
Positive share, +10 percentage points	2.85	1.13, 4.57	.001
Negative share, +10 percentage points	2.90	1.25, 4.55	.001
Log message count	0.19	−0.34, 0.72	.471
Previous five-day volatility	0.04	−0.02, 0.11	.203
Market volatility index	0.34	0.26, 0.42	<.001

The joint model associates both positive and negative sentiment with higher prospective volatility, conditional on the included controls. A ten-percentage-point increase in either sentiment category corresponds to approximately 2.9 additional volatility percentage points in this specification. Discussion intensity, however, lacks a statistically distinguishable partial effect once both sentiment shares enter simultaneously. The very strong inverse correlation between sentiment shares raises multicollinearity concerns and makes these conditional estimates sensitive to specification; statistical significance should therefore not be mistaken for a stable substantive mechanism.

Individual-predictor models illustrate the importance of distinguishing model-dependent coefficients from robust empirical relationships. When added separately to the benchmark, positive sentiment is not statistically associated with future volatility ($p = .995$), and negative sentiment is also insignificant ($p = .227$). Log message count becomes statistically significant ($p < .001$) when entered without the two sentiment shares. These reversals suggest that shared variation among textual indicators strongly influences the estimated contributions of individual measures within the illustrative panel.

Table 4. Illustrative Forecast Evaluation Using the 2024 Holdout Sample

Model	Training stock-days	Test stock-days	RMSE	MAE
Market-variable benchmark	2,247	741	4.368	3.546
Benchmark plus sentiment and attention	2,247	741	4.392	3.554

Chronological validation provides a stricter assessment of predictive usefulness. Models estimated on 2021–2023 stock-days were evaluated against observations from 2024, without re-estimating coefficients on the holdout period. The sentiment-augmented model produces slightly higher root mean squared error and mean absolute error than the conventional benchmark. Its RMSE increases by approximately 0.53%, indicating no forecasting improvement in this particular simulated sample. In-sample significance thus fails to translate into demonstrable out-of-sample predictive advantage.

Three simulated event windows illustrate how attention spikes may coincide with changing volatility. The GameStop illustration covers January 13–February 4, 2021; the AMC window covers May 24–June 15, 2021; and the BlackBerry comparison uses January 13–February 4, 2021. Each interval comprises 16 eligible trading sessions. The dates correspond to periods of heightened public interest in meme-stock activity, but the numerical observations shown here are synthetic demonstrations rather than reconstructions of actual historical message counts or prices.

Table 5. Simulated Event-Window Comparisons

Case	Mean messages/day during window	Outside window	Future volatility in window (%)	Outside window (%)
GME	13,784	2,892	18.13	13.42
AMC	4,502	1,984	18.64	12.66
BB	1,132	528	13.12	8.90

Event-window descriptions show marked increases in discussion intensity and future volatility relative to each stock's remaining sample. GameStop receives nearly five times its comparison-period messages, while its mean future volatility rises by 4.71 percentage points. AMC displays a smaller relative discussion surge but a larger volatility difference of 5.98 points. BlackBerry similarly shows increases in both indicators, although at lower absolute levels. The heterogeneity indicates that equivalent growth in online participation need not produce equivalent changes in market volatility.

The GameStop illustration associates unusually intense discussion with above-average positive sentiment, consistent with a stylized episode of collective enthusiasm. The AMC illustration instead contains relatively weaker positive sentiment and stronger negative sentiment during its selected window. Despite this contrast in emotional composition, both windows exhibit elevated future volatility. The result suggests a broader possibility: disagreement, uncertainty, and intense attention may accompany volatility even when the dominant emotional direction differs across securities.

Case comparisons cannot isolate social media effects from concurrent market events. Short-interest dynamics, option activity, liquidity constraints, brokerage restrictions, and company-specific announcements may influence prices and social media narratives together. The proposed model controls for several market conditions but does not capture all such mechanisms. Event-window contrasts are therefore best interpreted as descriptive illustrations of intertwined financial and communicative activity, not evidence that online messages initiated or sustained particular price movements.

The illustrative results portray a differentiated relationship between online sentiment and meme-stock volatility. Higher discussion volume generally accompanies higher volatility in descriptive comparisons, while sentiment coefficients depend strongly on which textual indicators appear together in the regression. The volatility index retains a positive conditional relationship, emphasizing the relevance of wider market uncertainty. The comparison of pooled statistics, stock-specific examples, and conditional estimates demonstrates why isolated correlations can misrepresent the underlying complexity.

The principal analytical finding is the contrast between conditional statistical significance and unsuccessful out-of-sample forecasting. A model may fit historical volatility more closely without providing more accurate predictions for a subsequent year. Strong sentiment

collinearity, overlapping forecast windows, nonrandom stock selection, and feedback between prices and discussion further restrict interpretation. These simulated findings establish an internally testable reporting template only. Empirical conclusions, journal-ready tables, and substantive policy implications require authorized Reddit data, verified market observations, and reproduction of the stated analyses.

The illustrative findings portray meme-stock volatility as related to online attention but not readily explained by sentiment alone. Across 2,988 simulated stock-day observations, GameStop exhibits the highest mean five-session volatility, followed by AMC Entertainment and BlackBerry. The pooled correlation between message intensity and subsequent volatility is positive ($r = 0.383$). These patterns describe constructed data rather than measured market outcomes.

Stock-specific comparisons reinforce the descriptive association between concentrated discussions and elevated risk. GameStop's highest-attention quartile shows mean future volatility of 14.34%, against 12.91% in its lowest quartile. Comparable contrasts appear for AMC and BlackBerry. Such comparisons remain unadjusted, however, and may reflect common reactions to price shocks, company announcements, or broader market uncertainty rather than an independent influence of Reddit discussions.

The panel specification presents a more complicated account. Positive and negative sentiment shares appear significant when entered together, whereas message intensity is not statistically distinguishable from zero after controlling for the sentiment measures and market conditions. Separate specifications produce different conclusions: neither sentiment share is individually significant, while discussion intensity becomes significant. This instability is central to interpreting the illustrative evidence.

Predictive validation further weakens strong conclusions about sentiment. Adding online indicators increases the simulated holdout root mean squared error from 4.368 to 4.392, despite improving in-sample explanatory fit. The difference is modest but directionally unfavorable. The results consequently demonstrate why correlations, regression significance, and forecasting accuracy must be evaluated separately before claiming that online sentiment identifies future risk across distinct market conditions.

The positive descriptive relationship resembles Chouaibi, (2022) finding that internet stock-board messages contained information about market volatility. Their study also associated disagreement with greater trading volume. The present illustration extends that question to Reddit-era meme stocks, but cannot reproduce their empirical contribution because its figures are simulated and its measurement strategy differs substantially from theirs.

Attention-based interpretations are consistent with Zhang, (2024), who established search activity as a distinct measure of investor attention, and S. Wang, (2022), who documented attention-induced trading among Robinhood users. Neither study implies that counting posts is sufficient for reliable volatility forecasting. The illustrated model's weak out-of-sample performance therefore qualifies, rather than contradicts, theories connecting salience with speculative trading.

López-Morales, (2023) examined GameStop's intraday returns using millions of Reddit comments and a platform-adapted sentiment dictionary in a highly concentrated episode. Their design emphasizes the importance of tone, timing, and financial slang. The current framework considers five-session volatility instead of minute-level returns, making direct coefficient

comparisons inappropriate. Differences in outcome definitions and temporal aggregation could explain divergent estimates without requiring either substantive explanation to be rejected.

The interpretation also complements Agyei, (2022) evidence linking pessimistic media content with price pressure and trading activity. Hajek, (2023) connected WallStreetBets attention with greater investor risk-taking using individual trading records. These studies supply stronger empirical grounding than simulated estimates. Taken together, they motivate further testing, while leaving open whether any single sentiment indicator contributes stable incremental forecasting information.

The illustration signals a distinction between information diffusion and information quality. A rapid increase in comments may reveal collective interest, yet message volume does not establish whether participants possess new fundamental information. Posts can express enthusiasm, uncertainty, humor, disagreement, or reactions to events already reflected in prices. Interpreting every discussion spike as an informed trading signal would therefore overstate its financial meaning.

The conflicting sentiment coefficients signify an additional measurement problem. Positive, negative, and neutral shares form a composition whose parts must sum to one. Changing one category necessarily affects the remaining categories, and the reported negative correlation between positive and negative shares is exceptionally strong. Conditional coefficients can consequently depend on coding choices and omitted reference categories rather than stable behavioral relationships. This complicates substantive economic interpretation.

The failure of the sentiment-enhanced model to outperform its benchmark signals a distinction between explaining the past and forecasting the future. Historical sentiment may capture the atmosphere accompanying an episode without predicting later uncertainty once conventional indicators are observed. The simulation does not establish that online signals are useless; it indicates that incremental value requires demanding temporal validation instead of reliance on significant fitted coefficients.

The comparison across three securities also points toward contextual rather than universal mechanisms. GameStop, AMC, and BlackBerry differ in trading histories, investor constituencies, and exposure to speculative narratives. Reinwald, (2023) argued that sensitivity to investor sentiment can depend on valuation uncertainty and limits to arbitrage. Their framework cautions against assuming a constant social media effect across assets.

The principal theoretical implication is the need to separate investor attention, sentiment direction, and market risk. Behavioral finance can explain why shared narratives attract trading interest, yet efficient price adjustment and information feedback may weaken simple predictive relationships. A useful account must allow sentiment to respond to volatility as well as potentially precede it, rather than treating communication as an automatically exogenous market force.

For financial analysts, the illustration discourages the use of sentiment dashboards as standalone trading or volatility forecasts. Reddit indicators might serve as supplementary measures of unusual attention, provided their accuracy is tested against appropriate benchmarks. Trading strategies based on apparently significant in-sample coefficients could create false confidence, particularly when performance deteriorates across later periods or different securities.

For regulators and market surveillance teams, elevated discussion activity could justify closer contextual assessment but should not be equated with manipulation. The Securities and

Lyócsa, (2022) GameStop report described interacting forces including short interest, substantial trading volume, retail attention, and brokerage restrictions. Surveillance systems should therefore integrate market microstructure evidence and clearly distinguish lawful collective discussion from potentially abusive conduct.

For researchers, the methodological implication is that prediction and explanation demand different evidentiary standards. Explanatory associations require transparent controls, sound inference, and careful causal language. Forecasting claims additionally require well-designed chronological holdouts, realistic transaction constraints when relevant, and comparison with strong baselines. The illustrative case shows how an apparently informative textual feature may fail the second standard despite seeming successful under the first.

One plausible mechanism is feedback between market movements and online engagement. A sudden price increase draws attention, encourages more posts, and may stimulate trading, which can generate further volatility. Falling prices can produce equally intensive discussions expressing loss, anxiety, or disagreement. This two-way process makes the same observable correlation compatible with several competing causal stories.

Another explanation concerns sentiment classification. General-purpose lexicons may misunderstand financial slang, irony, or expressions such as “diamond hands,” whose meaning depends on investing culture. Y. Chen, (2024) addressed this challenge by adapting their dictionary to Reddit language. Classification error can blur distinctions between optimism and pessimism, while daily averaging can conceal rapidly changing intraday conversations.

Statistical dependence offers a further explanation for coefficient instability. Sentiment proportions share a denominator and cannot vary independently, creating compositional constraints. Multiple related predictors can absorb overlapping variation, causing individual estimates to change when variables enter together. Five-session future-volatility windows also overlap, making successive observations dependent. Robust uncertainty estimates require techniques suited to this structure, especially with only three sampled securities.

Predictive deterioration may additionally arise from changes in market regimes. Relationships learned during the extraordinary speculative conditions of 2021 may be poorly suited to quieter or structurally different periods in 2024. Market uncertainty, liquidity conditions, platform participation, and regulatory responses may change together. A single constant-coefficient model might consequently average away event-specific relationships while generating unstable predictions during new episodes. Their practical value remains context dependent.

The immediate research priority is to replace illustrative observations with authorized historical Reddit records and verified stock-market data. Researchers should publish sampling rules, timestamp conventions, missing-data assessments, and measures of coding reliability. The final analysis should report actual sample sizes and distinguish observable associations from speculative causal mechanisms, without transferring numerical conclusions from the simulation into the empirical manuscript.

Future models should treat sentiment categories as compositional measures and test alternative representations, including net sentiment, disagreement, and theoretically justified log-ratio transformations. Domain-adapted dictionaries and manually validated classifiers would help assess whether conclusions depend on textual measurement. High-frequency analyses could explore whether information appears before, during, or after price changes more clearly than daily aggregates.

Greater attention to research design is equally necessary. Rolling-window validation, stock-level holdouts, alternative forecast horizons, and appropriate dependence-robust inference could establish whether reported effects survive replication. Broader asset samples would permit meaningful evaluation of heterogeneity and reduce dependence on three famous cases. Causal claims would require a credible identification strategy that addresses simultaneous price and communication shocks (Si, 2022; Y. Wang, 2023).

The broader agenda is to develop risk monitoring that combines credible online indicators with conventional market information without overstating what either source reveals. Practitioners should communicate forecast uncertainty and avoid interpreting social enthusiasm as proof of impending volatility. The simulated results ultimately support a disciplined research question, not an empirical verdict: when, for which securities, and under what conditions does social media sentiment add reliable predictive information?

CONCLUSION

The central finding of this illustrative study is that social media activity and meme-stock volatility can be related without yielding dependable volatility forecasts. In the simulated panel covering GameStop, AMC Entertainment, and BlackBerry, higher discussion intensity was associated with greater subsequent price variability in descriptive comparisons. Regression estimates nevertheless changed materially when positive sentiment, negative sentiment, and message volume were modeled jointly or separately. Although the expanded specification explained slightly more historical variation, it performed worse than the market-variable benchmark on the 2024 holdout sample. This contrast is the study's most important analytical insight: statistical association, explanatory fit, and predictive accuracy represent different forms of evidence. The reported numerical results arise from simulated observations and therefore demonstrate a research framework rather than establish empirical properties of meme stocks.

The proposed contribution is primarily conceptual and methodological. Conceptually, the framework treats online attention, emotional polarity, and volatility as separate constructs that may interact through investor behavior and market feedback rather than as interchangeable expressions of speculative enthusiasm. Methodologically, it combines stock-day sentiment indicators, conventional financial controls, stock-specific comparisons, dependence-aware estimation, and chronological out-of-sample evaluation. This approach makes it possible to test whether social media measures contain information beyond that already represented by past volatility, trading conditions, and broader uncertainty. The sensitivity of estimated sentiment effects to model specification also highlights the importance of handling correlated sentiment shares and checking classification quality. These features offer an analytical template for investigating digitally mediated investment behavior, not a verified new model of price formation or evidence that online conversations independently cause volatility.

The principal limitation is the absence of an observed, independently validated research dataset. Simulated message counts, sentiment distributions, regression coefficients, and forecasting errors cannot substantiate claims about actual investor behavior or historical market outcomes. The proposed sample of three prominent United States meme stocks would also constrain generalizability, while Reddit-only coverage could omit influential conversations elsewhere. Automated sentiment classification may misinterpret sarcasm and investing jargon; overlapping volatility windows and reciprocal relationships between prices and posts further complicate inference. Future research should obtain authorized historical posts and verified

market data, expand comparisons across securities and platforms during changing market conditions, and assess domain-adapted sentiment models against manually coded examples. Preregistered specifications, rolling-window validation, alternative volatility horizons, and credible identification strategies would clarify the robustness, predictive usefulness, and possible causal pathways of observed relationships. Empirical conclusions should be reserved until these steps are completed.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used Google Asssisted to assist inimproving grammar, language quality, and overall readability of the text. After using this tool, the author(s) Carefully reviewed and edited the content as necessary and take full responbility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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