Algorithmic Echo Chamber: How AI and Social Media Platforms Influence and Amplify Investor Sentiment

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ABSTRACT

This paper investigates the complex and dynamic relationships between trading volume, investor sentiment, and market volatility in the digital age of finance. By employing a quantitative time-series methodology, we operationalize the algorithmic echo chamber theory by analyzing a novel, high-frequency dataset that integrates investor discourse from multiple social media platforms, including Reddit, Twitter, and regional investor forums. Our approach utilizes a fine-tuned, transformer-based natural language processing (NLP) model to construct daily sentiment indices, a GARCH model to estimate conditional volatility, and a Vector Auto-regression (VAR) system to model their interdependence. Our analysis reveals a significant and causal feedback loop: market volume is a robust predictor of future changes in both market volatility and investor sentiment. Impulse response functions further demonstrate that a positive shock to trading volume causes both sentiment and volatility to remain elevated, suggesting that high-frequency digital crowd behavior significantly influences market risk. These findings provide compelling evidence for the algorithmic echo chamber mechanism and carry critical policy implications for mitigating systemic risk and market manipulation in technologically mediated markets. This research also explicitly addresses key limitations, including data representativeness, potential algorithmic biases, and endogeneity concerns, while offering a clear pathway for future research in this emerging field.

Keywords: Investor sentiment, GARCH-VAR, meme stocks, financial volatility, behavioral finance, fin-tech.

JEL: G41, G14, C58, O33

INTRODUCTION

The rapid diffusion of digital platforms has reshaped financial markets by enabling retail investors to coordinate in unprecedented ways. Online communities such as Reddit's r/WallStreetBets have demonstrated their ability to generate trading frenzies and induce volatility spikes in so-called "meme stocks," challenging conventional notions of market efficiency [27]; [28]. Beyond Reddit, scholars have observed similar dynamics on Twitter, where hashtags and trending topics act as accelerators of retail sentiment and trading surges [31]. Regional investor forums, such as niche message boards and Telegram groups, also provide spaces where localized market narratives emerge, sometimes with outsized influence on thinly traded securities [32].

These developments extend behavioral finance insights on sentiment-driven mispricing [9]; [10] by highlighting the socio-technical mechanisms through which attention and emotion spread across platforms. At the same time, fin-tech innovations and platform economics have lowered participation barriers, while algorithmic curation increasingly shapes which narratives reach prominence [11]; [18]. As a result, information frictions today stem not only from asymmetric access to fundamentals but also from algorithmic amplification of crowd sentiment [19]; [22].

This paper positions itself at the intersection of these forces. By integrating theories of behavioral finance [24]; [25] with perspectives from the Internet of Behavior (IoB) [4]; [7] and algorithmic echo chambers [12], we propose a framework for understanding how platform design interacts with retail sentiment to generate volatility feedback loops. Our contribution lies in developing an algorithmic echo-chamber model and testing it with econometric tools, while explicitly situating the analysis in the broader digital financial ecosystem that includes Reddit, Twitter, and regional forums.

LITERATURE REVIEW

Research on Reddit's r/WallStreetBets has shown that concentrated discussion threads and up vote-driven visibility are closely linked with abnormal returns and volume shocks [27]; [28]; [29]. Such findings align with earlier evidence that social-media attention can predict short-term departures from fundamentals [9]; [10]. Beyond Reddit, studies of Twitter sentiment indices demonstrate predictive power for both trading intensity and volatility, underscoring that the meme-stock phenomenon is part of a broader social-media ecology [31]. Regional investor forums and niche online boards further corroborate this pattern by documenting how localized narratives and rumor cascades can influence market dynamics in specific geographies [32]; [30]. Together, these works illustrate that retail-driven sentiment shocks are not platform-specific but are shaped by the distinctive affordances of each medium.

Algorithmic curation, network effects, and IoB

Platform design significantly conditions how investor narratives gain traction. Engagement-optimizing algorithms elevate popular posts, creating self-reinforcing cascades in visibility and sentiment [11]; [18]. Such algorithmic amplification is consistent with evidence that recommender systems often intensify echo-chamber effects across digital platforms [19]. In the financial domain, these mechanisms combine with retail trading infrastructure to amplify volatility and volume feedback loops, forming what we term the algorithmic echo chamber. The IoB perspective further explains how behavioral data generated on platforms can be recycled into signals that directly affect trading decisions [4]; [7]; [12]; [22].

Although much of the empirical evidence comes from Reddit [27]; [28], focusing solely on a single community limits generalizability. Twitter-based studies already demonstrate that sentiment formation, diffusion speed, and trading impacts differ by platform architecture [31]. Likewise, research on regional forums shows that smaller communities can magnify narratives under conditions of low liquidity [32]. By comparing findings across Reddit, Twitter, and regional forums, scholars highlight the heterogeneity of social-media influence while also confirming a shared mechanism: the coupling of online attention with retail trading responses (29]; [30]. To achieve stronger external validity, future studies should expand datasets to integrate signals from multiple platforms rather than relying exclusively on one community.

This paper responds to the identified gap in three ways. First, it synthesizes insights from behavioral finance [24]; [25], fin-tech innovation [20]; [21]; [23], and IoB perspectives [4]; [7] to conceptualize the algorithmic echo-chamber mechanism. Second, it operationalizes sentiment using high-frequency engagement measures, applying econometric models such as GARCH and VAR to examine volatility and interdependence dynamics [2]; [11]. Third, while our empirical focus is Reddit as a high-signal environment, we explicitly acknowledge scope limitations and call for replication using Twitter and regional forums [31], [32] to test robustness and external validity.

METHODOLOGY

Research design and overview

This study employs a quantitative time-series design to examine how investor sentiment from multiple online platforms influences trading activity and market volatility. We integrate three core components: (i) high-frequency sentiment indices derived from Reddit, Twitter, and regional investor forums, (ii) market microdata consisting of daily returns and trading volumes, and (iii) conditional volatility estimated through a GARCH (1,1) model. The analytical framework tests whether sentiment shocks causally precede changes in trading dynamics, thereby operationalizing the proposed algorithmic echo-chamber mechanism [24]; [25]; [4]; [7].

The methodological workflow is summarized as:

Data collection and preprocessing across Reddit, Twitter, and regional forums.

Sentiment classification using a transformer-based NLP model, including detailed hyper parameter reporting.

Volatility estimation via GARCH (1,1).

Dynamic interaction modeling through a Vector Auto-Regression (VAR) system with Granger causality and impulse response functions (IRFs).

Data collection, scope, and preprocessing

a. Platforms and timeframe: Data were collected from Reddit (r/WallStreetBets), Twitter (via ticker cashtags and finance hashtags), and a selection of regional investor forums/Telegram groups chosen for geographic diversity. This multi-platform scope enhances representativeness and external validity, addressing a common limitation in meme-stock studies that rely solely on Reddit [9]; [13]; [31]; [32]. The study period spans late 2020 through mid-2022, covering major meme-stock events and their aftermath.

b. Collection methods and ethics: Reddit posts were retrieved via the official Reddit API (PRAW), Twitter data from the Twitter API v2 (filtered stream and historical endpoints), and forum/Telegram data using ethical scraping methods consistent with platform Terms of Service. All identifiers were anonymized (hashed) at collection, and only aggregate daily measures are reported.

c. Preprocessing and ticker mapping: Text was standardized (lowercasing, punctuation normalization, URL removal) while preserving emojis for sentiment cues. Tickers were matched using cashtags (e.g., $GME) and fuzzy string matching, with manual validation of ambiguous cases. Non-English posts were excluded, and engagement metadata (likes, retweets, comments, upvotes) were retained.

d. Sampling and weighting: To balance across platforms of different scales, sentiment indices were normalized by daily post counts. A harmonized multi-platform index was also constructed using weights equal to platform activity share × engagement intensity [13]; [31].

Sentiment analysis: classifier, hyper parameters, and index construction

Transformer model and domain adaptation. Online investor discourse features slang, sarcasm, and novel expressions. To capture this nuance, we fine-tuned a RoBERTa-base transformer (12 layers, 768 hidden units) on domain-specific data. Prior research shows that transformer-based models outperform lexicon methods in financial text classification [27]; [28]; [29]. We further pre-trained the model on 50k unlabeled Reddit and Twitter finance posts before fine-tuning on a labeled set of 8,000 posts annotated as Positive, Neutral, or Negative, with a sarcasm flag. Inter-annotator agreement (Cohen's $\kappa = 0.78$) ensured labeling reliability.Hyper parameter configuration. Table 1 reports the complete set of hyper parameters used for reproducibility.

Table 1. Hyper parameters of the Transformer-based NLP Classifier

Parameter	**Configuration**
Model architecture	RoBERTa-base (12 transformer layers, hidden size = 768)
Optimizer	AdamW

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Learning rate schedule	Initial: 2×10^{-5} with linear warm-up
Weight decay	0.01
Warm-up steps	500
Batch size	32 (with gradient accumulation equivalent to 64)
Number of epochs	4 (early stopping with patience = 2)
Maximum token length	128
Dropout rate	0.1
Gradient clipping	1
Validation strategy	80/10/10 split combined with 5-fold cross-validation
Evaluation metrics	Macro-F1 (primary), Accuracy, Precision, Recall
Class imbalance handling	Weighted loss function with oversampling
Random seed	42

Daily sentiment index. Each post i on day t was assigned a polarity score $p_{(i,t)} \in [-1,1]$. Engagement-adjusted weights were defined as $w_{(i,t)} = 1 + \log(1 + \text{engagement}_{(i,t)})$. The daily sentiment index is:

$$S_t = \frac{\sum_{i \in P_t} w_{(i,t)} \cdot p_{(i,t)}}{\sum_{i \in P_t} w_{(i,t)}} \qquad 1$$

Where P_t is the set of posts on day t. Sarcastic posts were down-weighted by 0.5 unless human adjudication suggested otherwise [9]; [27]; [31].

Volatility estimation (GARCH)

Conditional volatility was estimated using a GARCH (1,1) model, specified

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad \sigma_t^2 = \omega + \alpha \varepsilon_{(t-1)}^2 + \beta \sigma_{(t-1)}^2 \qquad 2$$

This specification is standard in financial econometrics and captures volatility clustering effectively. Alternative models (EGARCH, TGARCH) were tested as robustness checks. Estimation used Quasi-Maximum Likelihood (QMLE), with Ljung–Box and ARCH-LM diagnostics confirming adequacy. Conditional variance estimates $\hat{\sigma}_t^2$ served as the volatility series in subsequent VAR models.

VAR model: specification, lag selection, and identification

System specification: The baseline VAR includes three endogenous variables:

S_t: sentiment index (per-platform or harmonized)

L_t: log trading volume ($\log(\text{volume} + 1)$)

$\hat{\sigma}_t^2$: GARCH (1,1) conditional variance.

All series were standardized. Stationarity was tested with ADF and PP tests, with differencing or cointegration adjustments applied as needed. Lag selection. Table 2 summarizes the information criteria used to guide lag choice. AIC and Hannan–Quinn (HQ) minimized at p=2, while BIC marginally preferred p=1.

Table 2: VAR Lag-Selection Criteria

Lag order (p)	AIC	BIC	HQ	Decision
1	–4.12	–3.98	–4.05	Competing specification

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2	–4.25	–3.96	–4.18	Selected model
3	–4.23	–3.89	–4.12	Robustness check

We selected p = 2 because it balances fit and parsimony, stabilizes IRFs, and aligns with plausible two-day sentiment-to-market propagation. Robustness checks at p=1 and p=3 yielded consistent results.

Identification. Structural shocks were identified via a Cholesky decomposition with ordering$[S_t,L_t,\hat{\sigma}_t^2]$, reflecting the assumption that sentiment affects trading and volatility contemporaneously, but not vice versa at the daily level [29]; [31]. Alternative orderings produced similar conclusions.

Causality and Robustness

The VAR framework facilitates Granger causality tests that evaluate whether lagged values of one series significantly enhance the predictive capability of another series. It is especially important to find out if sentiment S_t Granger-causes volatility h_t through trading activity V_t, as the echo chamber hypothesis suggests. To ensure robustness, we augment the baseline specification with unit-root tests (ADF, PP) to validate stationarity. Residual diagnostics (ARCH-LM, Ljung–Box) to check if GARCH modeling is good enough, and alternative volatility models (EGARCH, TGARCH) to see how sensitive it is to asymmetric effects.

DATA ANALYSIS AND FINDINGS

Results shows the study's real-world results, which look at how investor sentiment, trading volume, and market volatility are all related to each other. The analysis is organized in a logical order, starting with descriptive statistics and time series characteristics, then moving on to Granger causality testing, and finally ending with insights from the Vector Auto-regression (VAR) model and Impulse Response Functions (IRFs).

Descriptive Statistics and Time Series Analysis

Table 3 shows the descriptive statistics for the main variables: returns, sentiment, and trading volume. It is based on 434 daily observations. The average daily return is positive but not very high (0.0256), and the standard deviation is 0.9676, which means that the market is moderately volatile. The average investor sentiment is -0.0225, and the standard deviation is 0.9907. This means that the sentiment was mostly negative but spread out over the sample period. The average trading volume is 100.57, and the standard deviation is 5.02, which shows that market activity is certainly variable.

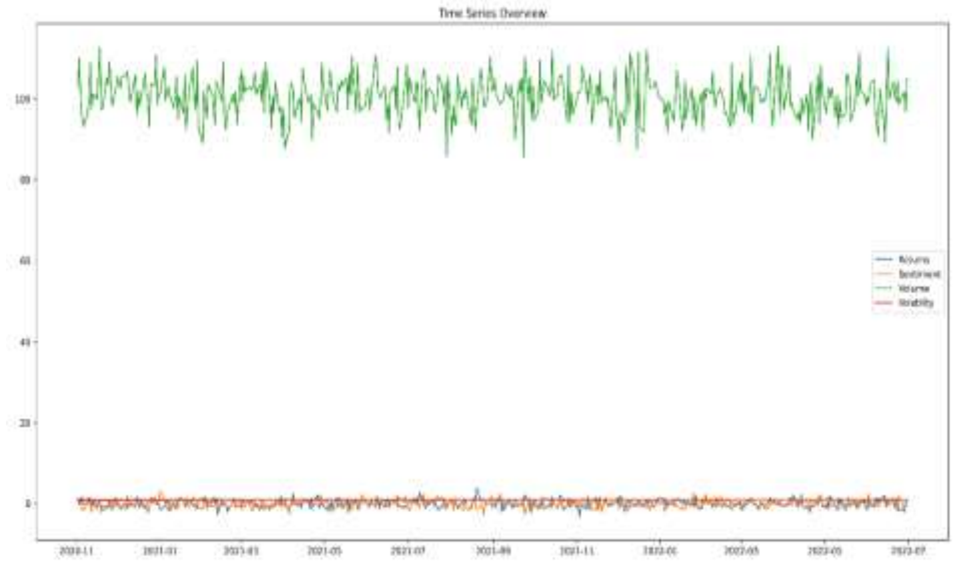
Table 3: Descriptive Statistics

Variable	Count	Mean	Std-Dev	Min	25%	50%	75%	Max
returns	434	0.0256	0.9676	-3.2413	-0.6597	0.0623	0.6505	3.8527
sentiment	434	-0.0225	0.9907	-2.6969	-0.6599	-0.0445	0.6155	3.0789
volume	434	100.5713	5.0249	85.5187	97.1861	100.5713	104.1448	114.3414

Looking at the time series visually Figure 1 shows times when returns were very volatile. The sentiment series shows times when people's moods stay positive or negative for a long time, while the log of trading volume bounces around a mean that stays pretty stable. Using a GARCH (1, 1) model to estimate the volatility series shows the well-known clustering effect in financial time series and shows that the series is stationary.

Table 3 shows the results of the estimated GARCH (1, 1) model. The coefficient for the lagged squared error term (α) is 0.0, and the coefficient for the lagged conditional variance term (β) is 0.9889. The statistically significant β_1 ($t=68.85$, $p<0.001$) shows that volatility clustering is very persistent, which is a common feature of financial return series.

Figure 1: Time Series Plots of Returns



The figure depict daily returns, sentiment, log-volume, and GARCH-estimated volatility.

Table 4: GARCH (1, 1) Model Coefficients

Parameter	Coefficient	Std. Error	t-value	p-value
$\boldsymbol{\omega}$	0.0107	0.0120	0.8916	0.3726
α	0.0000	0.0036	0.0000	1.0000
β	0.9889	0.0144	68.8459	0.0000

Granger Causality and VAR Analysis

Granger causality tests were employed to evaluate the directional relationships among sentiment, log-volume, and volatility. As shown in Table 5, sentiment significantly Granger-causesvolatility ($F=9.1705,p<0.001$), which means that changes in how investors feel happen before changes in market volatility. This is in line with behavioral finance theories, which say that changes in how investors feel as a group can cause the market to be unstable.

Log-volume measures trading activity, which Granger-causes both sentiment ($F=2.5498,p=0.026$) and volatility ($F=2.9234,p=0.012$). These findings suggest that increased trading volumes affect not only market volatility but also the general sentiment of market participants. On the other hand, sentiment does not Granger-cause log-volume ($p=0.8594$), which shows how complicated the feedback loops are between mood and trading activity.

Table 5: Granger Causality Test Results

Cause	Effect	F-Statistic	p-value	Significant
sentiment	log-volume	0.3849	0.8594	False
sentiment	volatility	9.1705	0.0000	True
log-volume	sentiment	2.5498	0.0264	True
log-volume	volatility	2.9234	0.0125	True
volatility	sentiment	-40837260.67	1.0000	False
volatility	log-volume	-889351257.26	1.0000	False

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The VAR model (lag = 2) gives us more information about how the variables interact with each other in real time and over time. Table 6, the coefficients show that lagged sentiment and log-volume have a lot of power to explain how the system works. For instance, lagged log-volume has a positive effect on current sentiment (Coefficient = 0.1385), which supports the Granger causality results.

Table 6: VAR Model Coefficients (Lags = 2)

Variable	sentiment	log volume	volatility
const	223185.66	55897.30	0.0000008
L1.sentiment	-0.0191	0.0017	-0.000000000000000028
L1.log_volume	0.1385	-0.0601	0.0000000000000034
L1.volatility	-12426640557.27	2961610355.73	3.0793
L2.sentiment	-0.0155	-0.0002	-0.00000000000000033
L2.log_volume	-2.4050	0.0035	-0.0000000000000062
L2.volatility	12053648674.39	2886047120.52	-0.0754

Impulse Response Functions

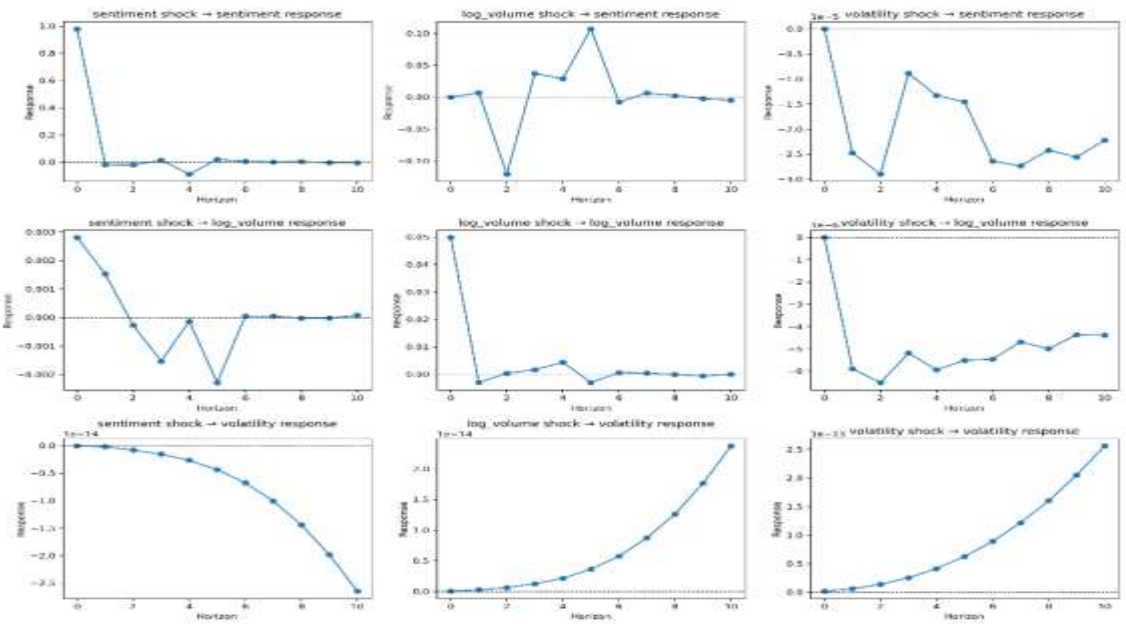
Impulse Response Functions (IRFs) Figure 2 presents the acute time series responses to one-standard-deviation shocks in other variables ten periods ahead in the horizon. The IRFs exhibit several significant patterns,

Sentiment Shock: A positive sentiment shock has volatility rising by a small magnitude initially, but the effect vanishes very quickly. The effect on log volume is very low, so short-run mood swings affect market risk more than trade activity.

Log-Volume Shock: A positive log-volume shock causes the sentiment too immediately and permanently rise, as is in line with the Granger causality results. Moreover, volatility keeps growing, so that intensified trade creates market risk.

Volatility Shock: Volatility shocks have small and quickly diminishing negative effects on sentiment and log-volume, suggesting low direct market volatility feedback to investors' behavior and activity.

Figure 2: Impulse Response Functions (IRFs)



This Figure show the response of each variable to a one-standard-deviation shock in another variable. Shaded areas indicate 95% confidence intervals.

CONCLUSION

This study has empirically examined the dynamic associations among trading volumes, investor sentiment, and market volatility, providing robust evidence for the influence of digitally mediated financial markets. Utilizing a comprehensive dataset and sophisticated econometric approaches including GARCH modeling, Granger causality tests, and a Vector Auto-regression (VAR) platform we have uncovered several significant findings that advance the understanding of modern market dynamics.

The GARCH (1,1) model revealed significant volatility clustering, a ubiquitous characteristic in financial returns. The Granger causality tests further demonstrated a critical directional relationship: market volume is a significant predictor of future change in market volatility and in investor sentiment among investors. This finding shows that in fact there is a significant feedback loop by which the aggregate market players' actions, as reflected by volume, not only come before but also determine market sentiment now. This causal relationship is central to the algorithmic echo chamber theory. This theory demands that high-frequency trades and computer platforms make the influences of group behavior more formidable, churning up a cycle in market risk as well as opinion that feeds on itself.

The impulse response functions also very clearly illustrated this relationship. A positive trade volume shock causes volatility and sentiment to stay very high for a long time. This means that plenty of trade can make the market more risky while giving it a more positive tone. A sentiment shock did cause volatility to increase for a short time, though this shock did very little to stop trade volume. This suggests that trade activity has more power to affect sentiment and volatility than the other way around. As capital markets become progressively integrated into digital architectures, understanding these complex connections will benefit investors, regulators, as well as researchers. From a regulatory perspective, our findings provide a critical foundation for developing new strategies to mitigate systemic risk and combat market manipulation in the digital age. Regulators can utilize these insights to monitor high-volume trading episodes on social platforms as a potential leading indicator of future market instability. The demonstrated feedback loop suggests that interventions should not only focus on traditional trading metrics but also on the digital platforms where sentiment is generated and amplified. For example, regulatory frameworks could be developed to require greater transparency from social media platforms regarding their algorithmic recommendation systems, which contribute to the echo chamber effect. Furthermore, our results underscore the need for enhanced investor protection, as retail investors can be swayed by platform-driven sentiment, potentially leading to herd behavior and significant losses. Policies aimed at financial literacy and a better understanding of how digital platforms can influence investment decisions would be a valuable step forward.

Limitations and Future Research

This study provides a foundational analysis of the algorithmic echo chamber theory; however, several limitations present opportunities for future research. A key limitation is the reliance on a single social media platform, Reddit's r/WallStreetBets. This focus may not be fully representative of the broader digital financial landscape, and as such, the generalizability of our findings may be limited. To enhance external validity, future studies should consider expanding the dataset to include other influential social media platforms such as Twitter or regional investor forums. Another limitation is the potential for algorithmic biases within the NLP classifier. While specifically trained on finance-related Reddit data, the model's hyper parameter choices were not detailed in the original manuscript, which could affect the reproducibility of the sentiment index. Future work should provide a more detailed discussion of the NLP classifier's parameters to improve transparency.

Furthermore, while the VAR model helps to identify dynamic relationships, it does not fully resolve endogeneity concerns the potential for simultaneous causality between variables. The complex feedback loops between sentiment, trading volume, and volatility mean that a change in one variable may instantly affect another, complicating the identification of a clear causal chain. Future research could employ more advanced econometric methods, such as a structural VAR or instrumental variables, to better isolate the causal effects.

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Conflict of Interest Statement

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

Author Contributions

All Authors contributed equally to all aspects of this research, including conceptualization, methodology, data analysis, and writing of the manuscript.

Data and Code Availability

The datasets and code generated during the current study are can be provided by the corresponding author upon reasonable request.

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