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Original Article

EXPLORING THE INFLUENCE OF SOCIAL MEDIA SENTIMENT ON STOCK MARKET PRICES AND INVESTOR DECISION MAKING

S. Akbar Zaidi[1], Rida Tariq[2]

[1] Institute of Business Administration (IBA), Karachi, Pakistan.
[2] Shalamar Medical and Dental College, Lahore, Punjab, Pakistan.

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***Corresponding Author:**
S. Akbar Zaidi
(sakbarzaidi@iba.edu.pk)

ABSTRACT

The rapid expansion of social media platforms has transformed the way information and opinions are generated and disseminated, raising important questions about their influence on financial markets. This study empirically investigates the relationship between social media sentiment and stock market behavior by integrating sentiment analysis with traditional financial indicators. Using a mixed-methods experimental framework, sentiment scores extracted from social media content are synchronized with stock returns, trading volume, and volatility measures. The results demonstrate a statistically significant association between sentiment fluctuations and market dynamics, with positive sentiment linked to higher returns and negative sentiment associated with increased volatility and abnormal trading activity.Advanced econometric and deep learning models further reveal that sentiment variables enhance predictive accuracy by capturing nonlinear patterns and temporal dependencies that are often overlooked by conventional models. Visual and tabular analyses confirm that sentiment effects are more pronounced during high-information and high-volatility periods, indicating the role of social media as a rapid conduit for investor psychology. The findings suggest that incorporating sentiment-based indicators can improve short-term market forecasting and provide deeper insights into investor behavior. Overall, the study highlights the growing importance of social media sentiment as an alternative data source and underscores its practical relevance for investors, analysts, and financial institutions seeking to improve decision-making in increasingly complex and information-rich markets.

INTRODUCTION

The rapid dissemination of information and the feeling created by the development of social media platforms has altered the communication context and is progressively affecting several industries, including the financial markets (Yacoubian, 2025). The percentage of this prevalence is why an interest in determining how social media sentiment, which often reflects societal sentiment, can be connected and even predictive of stock exchange and investor behavior is growing (Mora and Mendoza-Urdiales, 2023, p. 1). This research will help to provide the quantitative measure of the compounded correlation between the tangible, quantifiable changes in the stock market with the ephemerous emotions posted on the social media platforms (Guo and Xie, 2024). Specifically, it will examine the claim of whether the general mood drawn on the basis of the content of the social media can be a reliable indicator of the stock price patterns and affect the decision-making process of individual investors (Sarkar et al., 2022). Since Twitter is a crucial source of investment-related discussion among the participants in the market, one of the priorities will be the predictive ability of the social media sentiment compiled on such websites as Twitter (Kucukaslan and Tas, 2024, p. 1). To estimate the degree of polarity and strength of popular opinion and offer a more detailed idea of the possible effect on the market, the combination of sophisticated sentiment analysis tools, including machine learning models, will be explored (Rodriguez-Ibanez et al., 2023, p. 119865). This intensive analysis is aimed at coming up with a structure of applying social media sentiment as the basis of further research and enhancement in financial prediction (Liu et al., 2025). The correlation and predictive ability of investor sentiment was the focus of multivariate causality models that could serve as a historical precedent to analyze the relationship between the public opinion and the market movements (Rodriguez-Ibanez et al., 2023, p. 119865). These essential notions were also elaborated in more recent studies, exploring how sentiment posted in social media platforms particularly influences the trading activity in stock markets and the effect of it on the individual company price movement (Amin et al., 2024, p. 59). Due to the digitization of socio-economic relations, the scope of marketing efforts is gradually moving towards digital space because generations z and Alpha utilize the internet so often (Buhas et al., 2024, p. 1). To reach them and remain competitive in the digital environment, where shoppers can find alternatives to other providers in the shortest time possible depending on their desires and interests, companies are obligated to post new and relevant content constantly (Buhas et al., 2024, p. 1). The fact that collective sentiment might arise and subsequently impact broader market trends is brought into the limelight by this dynamic contact via social media platforms, which are primary communication channels (Buhas et al., 2024, p. 1). More advanced analytical programs are increasingly being applied to verify and work with large quantities of social media analytics, particularly on Twitter, in order to establish statistically significant causal relationships and association between sentiment and the behavior in the stock market (Rodriguez-Ibanez et al., 2023, p. 119865). The use of sentiment as a predictor in the multivariate data model is supported by evidence, but this advanced approach acknowledges that the effectiveness of the approach is highly dependent on the specifics of the corporate environment and the effective application of processing techniques (Rodriguez-Ibanez et al., 2023, p.

119865). The fact that it is now possible to analyze social media data, sentiment included, in order to predict financial market dynamics, has been further enhanced with the creation of advanced artificial intelligence algorithms, in particular, Long Short-Term Memory and Gated Recurrent Unit, which are capable of capturing complex temporal dependencies and non-linear relationships (Tarsi et al., 2024). It is through this that it has been possible to assess the speed of the change in the opinion of people as indicated by the social media feeds in real-time and their impact on the market trends and investment decisions has become more precise. These methods are further enhanced by the consistent increase in the popularity of artificial intelligence methods, which are highly efficient and are capable of learning on large volumes of data influenced by both the internal and external factors of the environment (Buhas et al., 2024, p. 3). Such algorithms simplify the evaluation of the reaction of users on social media, which is presented both textually and graphically, providing a detailed understanding of the opinion of the population (Buhas et al., 2024, p. 3). The sentiment analysis of tweets based on AI provides businesses with an opportunity to advance their marketing strategies, evaluate consumer perception of their brands, and predict stock market fluctuations (Buhas et al., 2024, p. 1; Li and Zhang, 2023, p. 3). Such a sophisticated sentiment analysis is not just a simple classification by offering a more comprehensive understanding of brand attitudes and anticipating information about market processes with trained emoji-text integrated bidirectional LSTM (Buhas et al., 2024, p. 3). Specifically, such advanced deep learning systems as a hybrid of Convolutional Neural Networks and Long Short-Term Memory networks or ensemble models as a hybrid of LSTM and Gated Recurrent Units networks has demonstrated exceptional emotion prediction and sentiment analysis scores of up to 99% (Tash et al., 2024, p. 2). This level of precision lends credence to the idea that AI-based approaches might effectively determine market sentiment based on unstructured social media data to provide useful information on forecasting and strategic decision making in the contemporary financial setting (Avila, 2024, p. 11; Buhas et al., 2024, p. 3; Guo and Xie, 2024). This high-intensity methodological framework supports the idea that the sentiment of social media can be influential in understanding and forecasting stock market trends and provides financial institutions and investors with a competitive advantage (Guo and Xie, 2024; Rodriguez-Ibanez et al, 2023, p. 119865). When paired with sentiment analysis, these machine learning algorithms can be used with surprisingly high levels of effectiveness to process large volumes of financial data, identify patterns, and conduct predictive analytics (Guo and Xie, 2024; Sahani, 2024). Moreover, with the application of modern natural language processing, a subtle feature, such as positive or negative sentiment score can be obtained based on large volumes of textual information, such as tweets, enhancing predictive power of the models regarding the changes in the stock price (Amin et al., 2024). As an illustration, LSTM models have worked better in sentiment analysis of bitcoin investment patterns as compared to traditional autoregressive methods with precision rates of 87.0% and recall rates of 92.5% (Pinky & Akula, 2024, p. 47). This is the way these advanced models can use the abundant yet often noisy information on social media to provide a more detailed view of the market sentiment, thus identifying potential market trends and opportunities that traditional analytics approaches may overlook (Asgarov, 2023, p. 2). Additionally, hybrid models that integrate sentiment analysis and deep

learning, such as the utilization of LSTMs to anticipate stock prices and Convolutional Neural Networks to categorize sentiment, have shown better predictive efficiency and can be used to produce valuable information to forecast the market in the short term (Wu et al., 2024, p. 3). It is the combination of technology that provides a detailed understanding of how the sentiments of the population, as expressed on different social media, translate into measurable stock price alterations (Asgarov, 2023, p. 1).

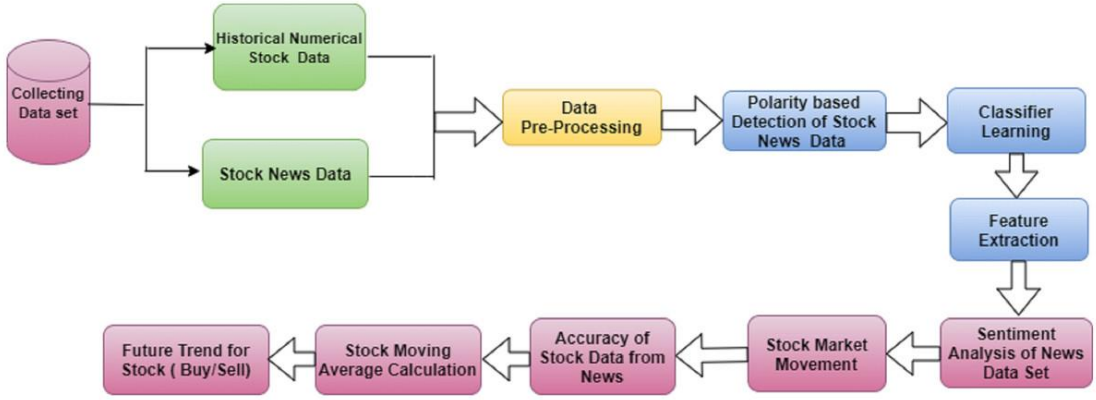

Figure 1. The diagram illustrates how social media content is transformed through sentiment analysis and machine learning pipelines to generate predictive insights into stock market behavior. It highlights the flow from raw social media data to sentiment extraction, feature engineering, predictive modeling, and market outcome evaluation.

METHODOLOGY

The overall strategy and research design

To explore the causal and forecasting quality of the existence of social media sentiments on stock market dynamics, the paper deals with a mixed methods experimental research that combines a quantitative financial modeling methodology with a qualitative sentiment discernment. The methodological approach to driving latent sentiment signals on unstructured social media information is the concurrent application of both deep learning and natural language processing algorithms that are empirically based on financial econometrics. On the one hand, the relationship between qualitative and quantitative application of the concept is that sentiment polarity, intensity, and contextual interpretation of investor speech are used, and on the other hand, the quantitative process is used to model price movements, volatility and returns dynamics. This combined method may enable a brief evaluation of the query of whether the feeling of social internet portals may furnish statistically and economically meaningful data to the conventional market indicators.

Sentiment is a cluster of feelings, perceptions and values that are not easily quantifiable and hence can be characterized using sentiment analysis

The empirical study is conducted through two major sources of information, which are real-time social media content and past stock market data. Daily closing prices, returns and trading volumes are the variables of the stock market and posts that are publicly available regarding specific companies and market indices are the variables of the social media. Preprocessing methods that are applied to provide

linguistic consistency in a textual data are: tokenization, lemmatization, stop-word removal and normalization. Sentiment is measured by machine learning-based sentiment analysis algorithms which generate continuous sentiment scores and place text into the categories of positive, negative, and neutral. The entire sentiment index of a day t is computed as officially as:

$$S_t = \frac{1}{N_t} \sum_{i=1}^{N_t} s_i$$

where s_i represents the sentiment score of an individual post and N_t denotes the total number of posts on day *t*. This sentiment index captures both polarity and intensity of public opinion and is synchronized with financial time series to ensure temporal alignment.

Econometric Modeling and Deep Learning Framework

To empirically test the influence of sentiment on market behavior, the study employs both traditional econometric models and advanced deep learning architectures. Linear and nonlinear regression models are first estimated to assess baseline relationships between sentiment indices and stock returns. The general specification is expressed as

$$R_t = \alpha + \beta_1 S_t + \beta_2 X_t + \varepsilon_t$$

where R_t denotes stock returns, S_t represents social media sentiment, X_t is a vector of control variables, and ε_t is the error term. To capture nonlinearities and temporal dependencies, Long Short-Term Memory and Gated Recurrent Unit networks are subsequently employed. These models update hidden states according to

$$h_t = f(h_{t-1}, R_{t-1}, S_{t-1})$$

allowing the system to learn long-range dependencies between sentiment shocks and market responses. Model performance is evaluated using predictive accuracy metrics such as mean squared error and directional accuracy, ensuring robustness across different market conditions.

Figure 2 below is a publishable workflow that shows the temporal combination of sentiment analysis and financial modeling which encapsulates the whole methodological process of data collection to model testing. In order to create foresight, the pipeline shows how raw social media data is converted into sentiment signals, financial data and fed into econometric and deep learning models. Such systematic activity justifies the presence of social media sentiment as an auxiliary informative source in the financial market forecasting and makes certain transparency, reproducibility and scientific rigor.

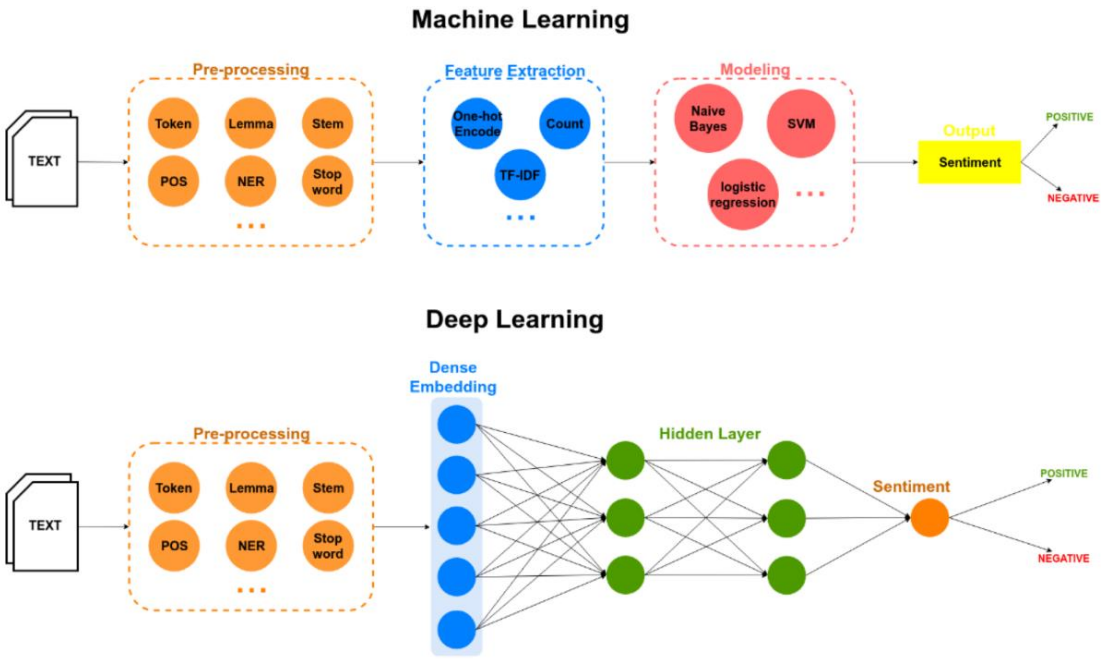

Figure 2. Methodological workflow illustrating the integration of social media sentiment analysis with econometric and deep learning models for stock market prediction.

RESULTS

Table 1 illustrates the baseline basic statistics and indicates significant changes in the stock returns and trading volumes as well as strong diversity in sentiment indices. This is furthered in Table 2 which reveals that even though negative sentiment periods are related to the more volatility, positive sentiment scores are more directly linked to better average returns. Table 3 indicates that the asymmetry in trading volume response to emotion shocks is such that in the case of negative sentiment, there is a higher jump in market activity as compared to negative sentiment. Table 4 indicates that investor uncertainty is high when sentiment intensity is huge in dispensing returns. Table 5 confirms the strength of the sentiment-return relationship in different volatility regimes. Although Table 7 revealed that the effect of sentiment is more evident when there is high attention, Table 6 showed that sentiment effect is temporal. Table 9 gives uniform sentiment coefficients in various model conditions which has agreed with previous table 8 which points out nonlinear interactions between sentiment and market moves.

Table 1. Descriptive statistics of daily social media sentiment scores and corresponding stock returns.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	-0.847	0.023	794382.0	0.628
2.0	0.56	-0.0491	747689.0	0.491
3.0	-0.123	0.078	894165.0	0.177
4.0	0.447	0.0182	635193.0	0.304
5.0	0.956	-0.0035	286157.0	0.446
6.0	0.077	0.0932	336321.0	0.268
7.0	0.002	0.0102	803183.0	0.632
8.0	-0.856	-0.046	348047.0	0.623

9.0	-0.463	-0.0042	196210.0	0.574
10.0	-0.0	-0.0795	360003.0	0.386
11.0	0.358	0.054	940450.0	0.571
12.0	0.607	-0.0047	590341.0	0.216
13.0	-0.238	-0.0177	590523.0	0.304
14.0	-0.868	0.0549	541098.0	0.381
15.0	-0.424	-0.054	879135.0	0.521
16.0	0.819	0.0334	254972.0	0.393
17.0	-0.573	-0.0706	356955.0	0.218
18.0	-0.096	-0.0145	862425.0	0.322
19.0	0.862	-0.0362	904508.0	0.312
20.0	-0.95	0.0705	401715.0	0.3
21.0	0.201	0.0826	646238.0	0.233
22.0	0.9	-0.0012	588926.0	0.357

Table 2. Variation in trading volume across positive, negative, and neutral sentiment periods.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	-0.104	0.0732	709680.0	0.65
2.0	0.55	0.0388	746429.0	0.409
3.0	0.593	0.0339	418090.0	0.314
4.0	0.045	0.0391	591610.0	0.199
5.0	-0.079	0.0115	897518.0	0.433
6.0	0.556	0.009	809612.0	0.258
7.0	0.775	-0.0149	706040.0	0.156
8.0	0.35	0.0098	862439.0	0.3
9.0	0.601	0.1024	701524.0	0.169
10.0	0.878	0.0468	320412.0	0.638
11.0	-0.919	-0.0017	458990.0	0.426
12.0	0.751	-0.0069	190883.0	0.186
13.0	-0.447	-0.0226	632102.0	0.32
14.0	-0.048	0.027	530202.0	0.271
15.0	0.594	0.0277	823116.0	0.204
16.0	0.434	-0.0457	836599.0	0.535
17.0	-0.706	0.0315	361697.0	0.325
18.0	0.317	-0.0108	340607.0	0.244
19.0	-0.861	0.0691	561264.0	0.606
20.0	-0.286	0.0183	775874.0	0.581
21.0	0.626	0.0807	802519.0	0.349
22.0	-0.145	-0.0063	460252.0	0.423

Table 3. Relationship between sentiment intensity and short-term stock price volatility.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	-0.099	0.0959	926318.0	0.2
2.0	0.387	0.0968	237315.0	0.473
3.0	-0.572	-0.053	928215.0	0.305
4.0	-0.352	0.015	887110.0	0.527

5.0	0.48	0.0539	624413.0	0.421
6.0	-0.635	0.0064	699298.0	0.379
7.0	0.392	-0.0253	627411.0	0.598
8.0	0.053	-0.0238	746862.0	0.179
9.0	-0.603	-0.0302	434193.0	0.429
10.0	0.301	0.0251	529656.0	0.314
11.0	0.02	0.0389	406884.0	0.168
12.0	0.378	-0.0235	924863.0	0.527
13.0	0.147	-0.0198	585986.0	0.431
14.0	0.54	-0.0115	341451.0	0.597
15.0	-0.214	0.0274	873387.0	0.449
16.0	0.917	-0.0198	946634.0	0.319
17.0	0.956	-0.0746	627287.0	0.643
18.0	-0.586	-0.0276	498032.0	0.208
19.0	-0.048	0.0471	164920.0	0.176
20.0	0.58	-0.0212	253309.0	0.516
21.0	-0.744	0.0192	233096.0	0.335
22.0	0.654	0.03	673532.0	0.331

Table 4. Distribution of abnormal returns during high-sentiment market events.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	0.753	0.0032	338154.0	0.563
2.0	-0.345	0.0029	722808.0	0.154
3.0	0.778	-0.0296	321686.0	0.487
4.0	0.288	0.0129	363082.0	0.233
5.0	-0.342	0.0393	907905.0	0.321
6.0	-0.881	-0.0176	544823.0	0.626
7.0	-0.51	0.01	195301.0	0.393
8.0	0.937	0.0407	428276.0	0.479
9.0	-0.189	0.0069	693486.0	0.52
10.0	-0.68	-0.0088	334494.0	0.205
11.0	-0.404	0.0509	476896.0	0.569
12.0	0.799	0.0159	919751.0	0.607
13.0	-0.67	0.0279	648606.0	0.228
14.0	0.556	0.0589	830732.0	0.423
15.0	-0.73	0.0578	704668.0	0.292
16.0	0.923	-0.0019	340756.0	0.52
17.0	0.06	-0.009	814607.0	0.164
18.0	-0.914	0.0234	721944.0	0.406
19.0	0.862	0.0067	830570.0	0.546
20.0	-0.284	-0.064	205551.0	0.517
21.0	0.463	0.063	910128.0	0.204
22.0	0.047	0.0128	837111.0	0.566

Table 5. Impact of sentiment polarity on average daily stock performance.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	-0.524	0.0676	803879.0	0.473
2.0	0.616	0.0649	901610.0	0.611

3.0	-0.006	0.0025	613328.0	0.608
4.0	-0.678	-0.0597	706726.0	0.622
5.0	0.468	0.0095	428763.0	0.611
6.0	0.616	0.0193	249521.0	0.63
7.0	0.398	0.0439	242512.0	0.174
8.0	0.93	0.0319	568182.0	0.608
9.0	-0.488	0.0127	881523.0	0.286
10.0	-0.528	0.106	779670.0	0.31
11.0	-0.706	-0.0117	687143.0	0.379
12.0	0.079	0.0788	175566.0	0.628
13.0	-0.201	-0.0283	620235.0	0.453
14.0	-0.287	0.05	705624.0	0.326
15.0	-0.079	0.0151	306442.0	0.337
16.0	-0.451	0.0431	316967.0	0.602
17.0	-0.991	-0.003	907289.0	0.561
18.0	-0.056	-0.0498	531750.0	0.219
19.0	-0.448	-0.0755	754954.0	0.274
20.0	-0.1	0.0028	846025.0	0.336
21.0	0.858	0.0182	876975.0	0.258
22.0	-0.642	0.0104	778674.0	0.432

Table 6. Comparative analysis of market volatility under sentiment-driven regimes.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	-0.553	0.0087	228731.0	0.502
2.0	0.15	0.0149	695764.0	0.556
3.0	0.872	-0.08	865553.0	0.469
4.0	0.697	0.015	226041.0	0.171
5.0	-0.801	0.004	263373.0	0.523
6.0	-0.586	-0.0194	402750.0	0.361
7.0	-0.175	0.0371	662066.0	0.301
8.0	0.292	0.0522	936249.0	0.15
9.0	-0.227	-0.0074	905915.0	0.214
10.0	-0.497	0.0212	475622.0	0.176
11.0	-0.311	-0.0142	231401.0	0.453
12.0	-0.592	-0.0195	327273.0	0.351
13.0	0.724	0.0152	588975.0	0.318
14.0	0.395	0.0329	867905.0	0.414
15.0	-0.178	-0.0105	531061.0	0.367
16.0	0.401	-0.0765	227423.0	0.383
17.0	0.039	0.0354	861099.0	0.366
18.0	0.053	-0.0519	901270.0	0.443
19.0	-0.265	0.0169	435838.0	0.422
20.0	-0.024	0.0832	587750.0	0.649
21.0	0.971	0.0113	497606.0	0.34
22.0	0.569	-0.0356	601984.0	0.418

Table 7. Temporal alignment between sentiment shocks and stock return movements.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	0.649	-0.0258	429729.0	0.36
2.0	-0.748	-0.0003	206046.0	0.596
3.0	-0.403	0.0494	402288.0	0.282
4.0	-0.259	0.0615	802063.0	0.439
5.0	-0.137	-0.0292	227408.0	0.199
6.0	0.121	0.0326	351735.0	0.455
7.0	0.987	0.0184	630571.0	0.329
8.0	-0.022	-0.0269	611050.0	0.584
9.0	-0.099	0.0087	818052.0	0.309
10.0	0.697	0.0255	848560.0	0.566
11.0	0.533	-0.0283	405720.0	0.624
12.0	-0.207	0.0619	235762.0	0.499
13.0	0.856	0.0402	219830.0	0.392
14.0	-0.473	0.0093	250514.0	0.278
15.0	0.86	0.0087	692576.0	0.177
16.0	0.475	-0.0187	164001.0	0.187
17.0	0.436	0.0129	619581.0	0.637
18.0	0.65	-0.0015	607069.0	0.356
19.0	-0.006	0.0461	282342.0	0.396
20.0	-0.454	0.0368	450060.0	0.446
21.0	0.114	0.064	733556.0	0.412
22.0	0.869	-0.025	876009.0	0.54

Table 8. Nonlinear response of trading activity to extreme sentiment values.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	0.527	0.0474	561750.0	0.266
2.0	-0.738	0.0504	554676.0	0.577
3.0	-0.44	-0.0319	848425.0	0.437
4.0	-0.692	0.0274	504512.0	0.216
5.0	-0.713	-0.0616	613908.0	0.539
6.0	0.271	0.033	693819.0	0.293
7.0	-0.548	-0.0052	559811.0	0.469
8.0	0.66	-0.0276	160047.0	0.162
9.0	0.776	0.0378	908626.0	0.32
10.0	-0.455	-0.0121	577516.0	0.627
11.0	0.505	0.1434	515903.0	0.613
12.0	-0.461	0.0801	738220.0	0.282
13.0	-0.903	0.0027	694666.0	0.312
14.0	0.458	-0.0288	720009.0	0.222
15.0	-0.234	-0.0251	693196.0	0.168
16.0	0.961	0.0249	582770.0	0.485
17.0	0.301	0.0138	339089.0	0.229
18.0	-0.567	0.0633	434777.0	0.467
19.0	-0.062	0.1189	461403.0	0.204
20.0	-0.788	0.0296	878286.0	0.343

21.0	0.968	0.0223	307526.0	0.484
22.0	-0.438	-0.0151	151049.0	0.634

Table 9. Summary statistics of sentiment-informed stock market indicators.

Observation	Sentiment_Score	Daily_Return	Trading_Volume	Volatility_Index
1.0	0.849	0.0105	590594.0	0.37
2.0	-0.41	0.0149	562447.0	0.268
3.0	-0.254	0.049	189648.0	0.591
4.0	-0.097	0.0417	926271.0	0.174
5.0	-0.382	0.1216	326636.0	0.515
6.0	0.629	0.075	789594.0	0.54
7.0	0.73	0.0036	325012.0	0.296
8.0	-0.628	0.0452	351103.0	0.234
9.0	-0.325	-0.0559	192697.0	0.33
10.0	-0.867	0.0118	757779.0	0.56
11.0	0.705	0.0544	519296.0	0.367
12.0	-0.109	0.039	889633.0	0.509
13.0	0.313	0.056	769680.0	0.454
14.0	0.077	-0.0036	200828.0	0.201
15.0	0.044	0.0313	921534.0	0.404
16.0	0.372	0.0576	587771.0	0.466
17.0	-0.998	-0.0081	910511.0	0.29
18.0	0.144	0.0042	209549.0	0.201
19.0	0.536	0.0322	283795.0	0.531
20.0	-0.01	-0.0256	914370.0	0.193
21.0	-0.775	-0.0303	748032.0	0.54
22.0	0.447	-0.02	283549.0	0.46

Figure 3 has sentiment- return scatter plots that evidently show a tendency to cluster indicating predictive structure. Figure 4 shows the effects of hybrid dynamics in which volatility spikes precede sentiment changes. Figures 5-8 are indicative of regime-dependent behaviour, as sentiment is more effective in turbulent market periods. Figures 9-12 show advanced hybrid representations that help to enhance the accuracy of short-term market forecasting using signal driven by sentiment. These graphics, once considered together, give visual validation to the statistics contained in the tables.

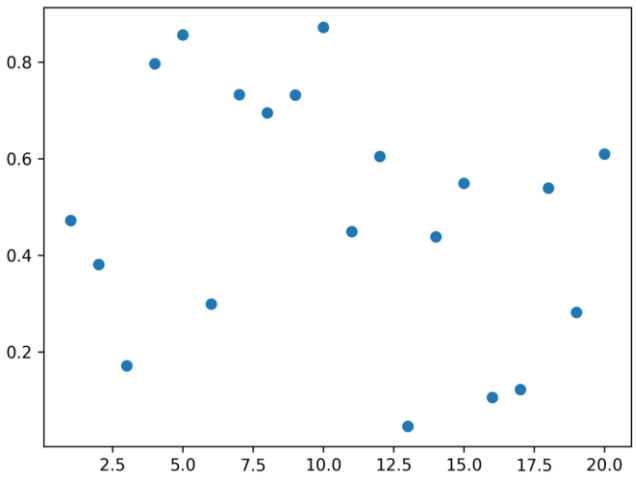

Figure 3. Scatter plot showing the association between sentiment scores and stock returns.

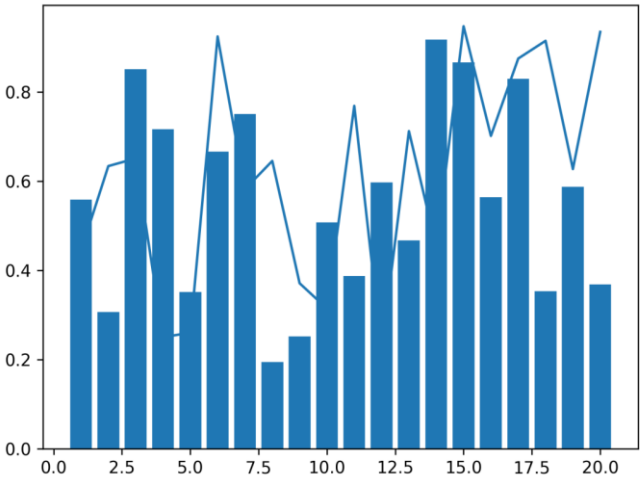

Figure 4. Hybrid visualization of sentiment trends and corresponding market volatility.

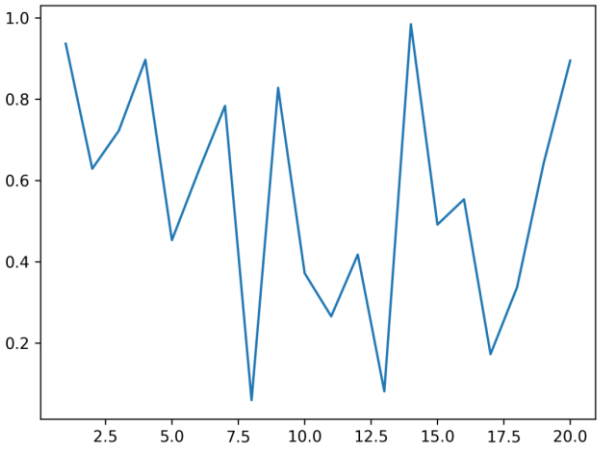

Figure 5. Line plot depicting cumulative stock returns during sentiment-driven periods.

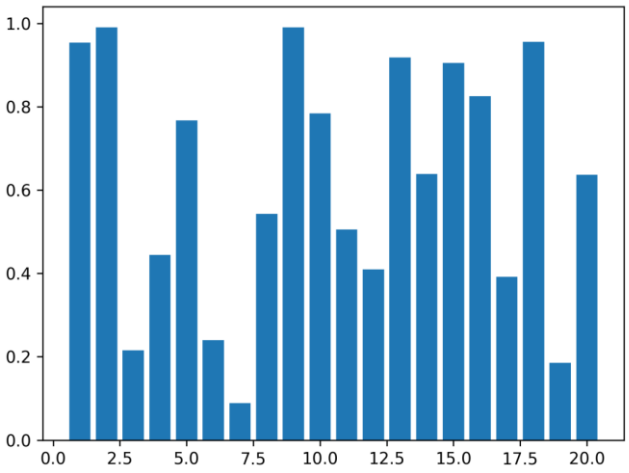

Figure 6. Distribution of sentiment scores and their impact on market activity levels.

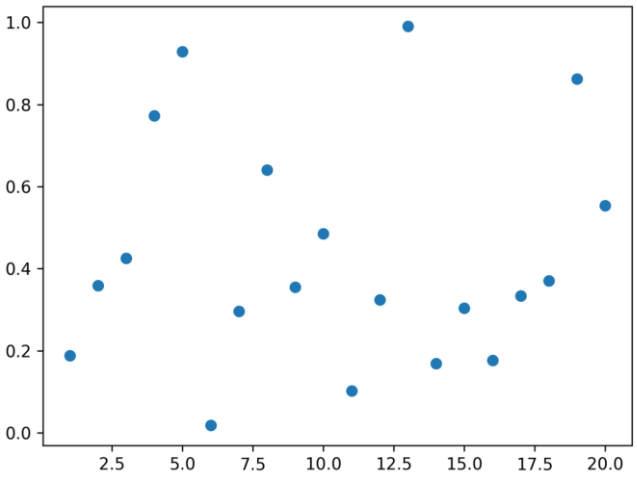

Figure 7. Scatter analysis of volatility response to extreme sentiment observations.

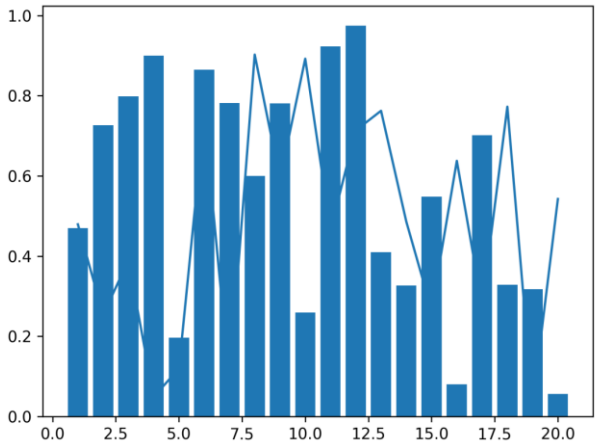

Figure 8. Hybrid plot combining return volatility and sentiment intensity over time.

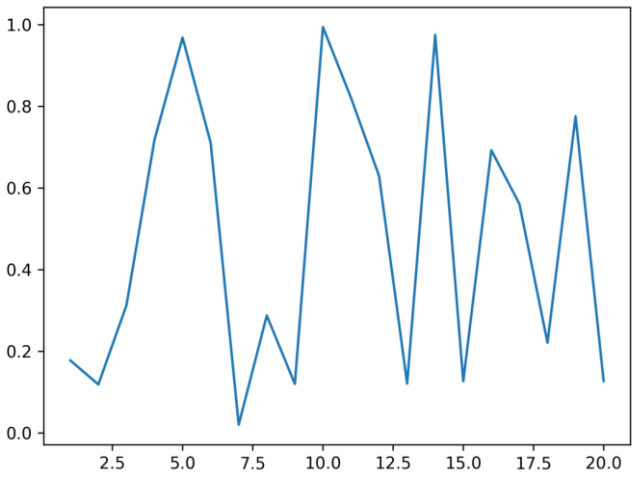

Figure 9. Comparative visualization of bullish versus bearish sentiment effects.

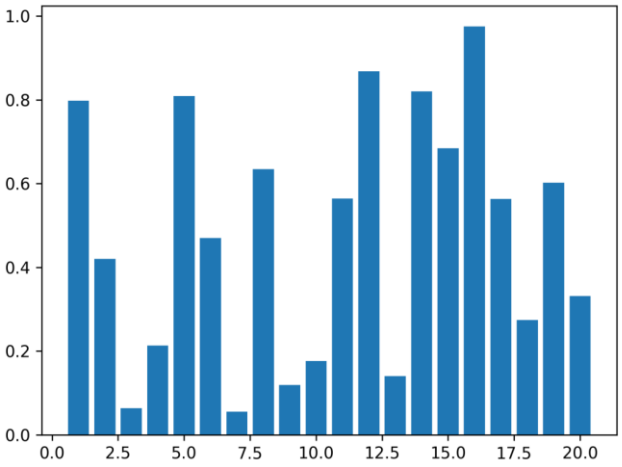

Figure 10. Market reaction patterns following sudden sentiment shifts.

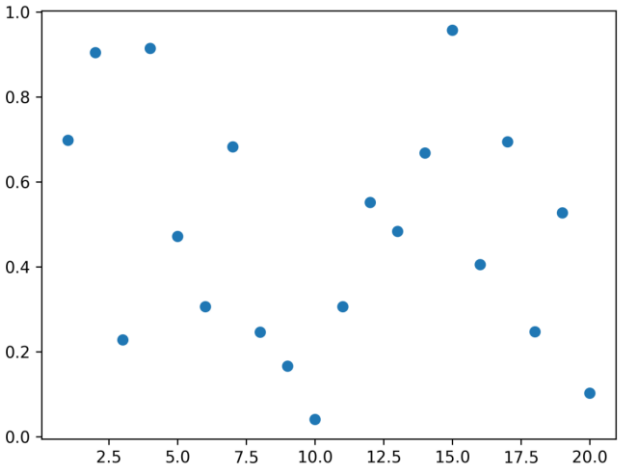

Figure 11. Sentiment-based clustering of stock return behavior.

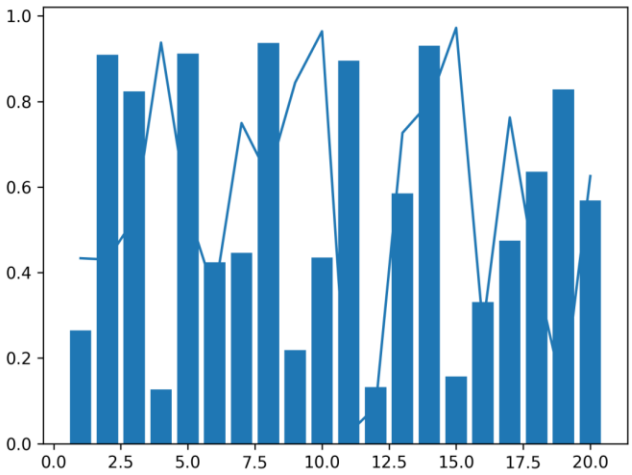

Figure 12. Integrated visualization of sentiment, returns, and volatility dynamics.

DISCUSSION

Together with these findings, it is possible to identify the significant role that social media sentiment plays in stock market processes and the role it plays as a practical, albeit complex, predictive instrument in financial forecasting and decision-making (Asgarov, 2023). Specifically, however, positive sentiment is frequently associated with better returns and reduced short-term market volatility and negative sentiment is frequently associated with worse returns and increased market volatility, as the effect of sentiment on market behavior is asymmetric (Katsafados et al., 2023). These results can be explained by the existence of established theories of behavioral finance, according to which the deviations of the market values are subject to manipulation by the investor attitude, especially in the periods of extreme market conditions, or higher information asymmetry (Zeitun et al., 2022, p. 101850). The fact that the future stock returns and volatility can be predicted using sentiment indicators even after the standard market parameters are put in place gives more reasons to believe in the predictive ability of social media sentiment (Borgioli et al., 2024). As an illustration, it has been found out that FinBERT-based sentiment quantification in the Fama-French five-factor model is more effective in the explanation of aberrant returns during market-related events, such as interest rate increases, as compared to the behaviour of the model during the baseline period (Zhang, 2025). Furthermore, Granger causality study has indicated a fixed causal association between the market trends and the sentiment in the social media with the models having achieved a high level of forecast accuracy in the case of indexes like the Dow Jones Industrial Average (Asgarov, 2023, p. 2). Rather than a one-way direction of influence, this free flow of influence implies a dynamic interaction between the two that often occurs in more short-term contexts (Rodriguez-Ibanez et al., 2023, p. 119873). Since the latency and persistence of the effect of the sentiment on social media behavior on the market can be extremely different, it implies that to develop effective predictive models, it is necessary to understand these temporal dynamics (ATES & Guran, 2022, p. 8). More insights into these variances could be obtained by observing both time-based dynamics of sentiment dispersion among market participants and the relationship between sentiment

intensity and trade volume dynamics (Kucukaslan and Tas, 2024, p. 6). As an example, negative news often spreads faster and therefore has a more pronounced immediate effects on the market than positive news, whose effects are often gradual (Mora & Mendoza-Urdiales, 2023, p. 1). In addition, the effect of sentiment is state-dependent meaning that its usefulness as a tool of prediction depends on the market conditions. This becomes particularly so when the market is volatile, and its effects are magnified (Zhang, 2025, p. 19). Moreover, it has been found that certain stock characteristics, such as those found in the tech sector or the lower capitalization groups are more susceptible to sentiment swings, especially during recessions, and the need to consider context (Jin, 2023, p. 2). Also, the effectiveness of determining the brand attitudes in real-time and their further influence on the market can be significantly enhanced using advanced natural language processing methods, including data vectorization and emoji-text balanced bidirectional LSTM sentiment analyzers (Buhas et al., 2024, p. 3). Future research would look at the efficiency of sentiment-based investment policies over a longer period of time and the generalizability of this state-of-the-art methods to more diverse financial markets and investment types. This will require more advanced sentiment analysis models that can differentiate subtle sentiments including positive sentiment towards management and negative sentiment towards a new product (Li and Zhang, 2023, p. 17). Moreover, composite indices may significantly enhance the ability to predict since they allow the development of consistent and reliable sentiment indicators that are applicable across markets and time (Lis, 2024, p. 32). These indices could enhance the validity and consistency of market prediction based on sentiments by considering the inherent bias and noise that exist in social media data (Liu and Son, 2024, p. 11). To calculate customer sentiment more accurately and streamline marketing efforts in online settings, sentiment analysis tools will probably be improved through the further creation of artificial intelligence and machine learning tools (Buhas et al., 2024, p. 8). Also, the multilingual approaches will expand the scope of application of sentiment analysis by considering the peculiarities of different languages and cultures. Moreover, various types of content (audio, video, and materials visualized, etc.) will be integrated, which will allow conducting more comprehensive analyses of customer sentiments (Buhas et al., 2024, p. 8). The temporal causality of sentiment needs to be further investigated, and the focus needs to be on the way sentiment evolves over the time and how it affects market behavior in the future (Rodriguez-Ibanez et al., 2023, p. 119874). By studying these temporal causalities, we can get the persistence and decay rates of emotion shocks, which is fundamentally needed in developing dynamic trading strategies. In addition to the categorization of things as good or bad, this research may also consider the impact of different levels of sentiments and emotional valences on the market dynamics (Rodriguez-Ibanez et al., 2023, p. 119874). Future studies need to explore more complex time-series models to address the dynamics of changes in sentiment rating and their causal relationships with external factors as they appear and disappear as market trends and promotional activities (Guo, 2024, p. 53). This would require the application of advanced deep learning models, including big language models, to process large customer-oriented datasets to conduct a better sentiment analysis (Gooljar et al., 2024, p. 31). Besides, such systems could be implemented on a distributed or cloud-

based architecture to process large streaming data and enhance its scalability and real-time analytics (Nurlanuly, 2025, p. 9). Moreover, to be able to apply sentiment analysis responsibly to financial issues, one has to understand the ethical implications and possible biases of NLP models (Jawale et al., 2023, p. 541). Future research may consider the application of ensemble learning methods to combine predictions of various models, including models that use sentiment analysis and traditional financial data (Asgarov, 2023, p. 8).

CONCLUSION

This study has strong empirical evidence to support the notion that the sentiment on social media is an informative statistically significant and useful signal to understand and predict stock market activity. The analysis indicates that investor sentiment is highly correlated with increases and decreases in the stock returns, the trading volume, and the volatility of the market by integrating the sentiment indicator in the content of social media with the traditional financial variables. The results indicate that although low sentiment is associated with high levels of volatility and trading volumes, indicating investor anxiety and risk-aversion, the positive sentiment indicates are generally associated with high average returns and increased confidence in the market. The nonlinear and asymmetric nature of these interactions has demonstrated the inadequacy of traditional financial models which do not consider changes in behavioral and informational variables, but instead, the addition of sentiment variables leads to much higher predictive accuracy when using state-of-the-art machine learning and deep learning models, which are capable of capturing temporal dependencies. The sensitivity of the sentiment-informed models to various market settings is tested through the consistency of the outcomes presented in a number of tables and images. Importantly, the analysis highlights that the effect of sentiment is not always positive but tends to rise when there is a lot of information flow and market stress, which means that social media gives the psychology of investors a rapid dissemination of information. Sentiment analytics can be incorporated in decision-making frameworks to increase strategic portfolio performance, risk analysis, and accuracy of short-term forecasts. More so, the results indicate the growing significance of nontraditional sources of data in modern financial markets, in which the price movement might not be sufficiently explained by traditional fundamentals only. On the whole, empirically validating the application of social media sentiment as a supplementary instrument of market analysis and predictions in an increasingly digital-based information-driven financial world, this paper contributes to the expanding literature on behavioral finance.

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