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The Long and Short-Term Effect of Social Media Manipulation on the NASDAQ Index

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Abstract

Social media's power to manipulate the financial markets has sparked significant debates, particularly regarding its impact on stock exchanges and cryptocurrency markets. This study investigates the influence of social media manipulation, specifically through Twitter, on the NASDAQ Composite index during its decline from December 1, 2021, to January 31, 2022. Utilizing daily data, the research emphasizes the direction of the relationship between Twitter sentiment and the NASDAQ index. Sentiment analysis, conducted using TextBlob, determines the positivity or negativity of the language used in tweets related to NASDAQ. The study tests the hypothesis of a long- and short-term relationship between the sentiment scores and the index. Time series analysis required ensuring stationarity, which was verified using modern and traditional unit root tests. Subsequently, an ARDL model was employed to examine these relationships. The findings reveal that social media manipulation via Twitter does not impact NASDAQ Composite prices in either the long or short term. Instead, price variations in the NASDAQ Composite index are significantly influenced by the sentiment expressed on Twitter.

Keywords: Twitter, Sentiment Analysis, ARDL Bounds Test, NASDAQ.

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1. INTRODUCTION

With the rapid advancement of technology, the profound impact of digitization has become increasingly evident, affecting not only social interactions but also key areas of the economy. While digitization offers numerous benefits, it also introduces significant challenges. Of particular importance is the role of social media, whose influence on the financial sector has been extensively examined (Chen et al., 2014; Zheludev et al., 2015). The manipulation of financial markets through social media platforms can often lead investors to make suboptimal decisions. Therefore, a comprehensive evaluation of multiple parameters is essential when making investment choices.

In response to these challenges, data mining techniques have been increasingly employed to enhance analytical capabilities in financial research. Traditional econometric methods alone may no longer be sufficient in this dynamic environment, highlighting the importance of monitoring patterns of human behavior. The widespread use of social media in finance offers unprecedented insights into investor sentiment and market dynamics.

Recent events, such as Elon Musk's involvement with Twitter and the cryptocurrency markets, underscore the profound impact of social media on financial markets. This study aims to investigate the long-term and short-term effects of manipulative activity on the NASDAQ Composite Index via Twitter. The analysis focuses on the period from December 1, 2021, to January 31, 2022—a time marked by significant fluctuations in the NASDAQ Composite following its peak. This timeframe provides an opportunity to examine the effectiveness of social media manipulation during market downturns.

This study seeks to determine whether the NASDAQ Composite Index is influenced by social media manipulation in both the short and long term, thereby contributing to the existing body of literature. While previous research in finance has primarily focused on time series and volatility analyses, exploring the relationship between stock price formation and sentiment analysis offers a novel perspective. What sets this study apart is its emphasis on the effects of manipulative social media activity—specifically Twitter sentiment—on the NASDAQ Composite Index. By integrating sentiment analysis with the ARDL econometric model, the research aims to provide empirical insights into the ways digital platforms shape investor behavior and market dynamics.

Methodologically, this study employs sentiment analysis of Twitter data (TSA) alongside an econometric analysis of the NASDAQ Composite Index (IXIC), with data sourced from Investing.com. To ensure the reliability of the data, stationarity tests—including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests—were applied. Additionally, the Fourier Augmented Dickey-Fuller (FADF) test was used to validate the stationarity results and to account for potential structural breaks. The findings indicate that the TSA series is stationary at level [I(0)], while the NASDAQ series is integrated of order one [I(1)], thus justifying the application of the Autoregressive Distributed Lag (ARDL) Bounds Testing approach for further analysis.

The rapid advancement of digital technologies has significantly transformed not only social interactions but also the structure and behavior of financial markets. Within this digital landscape, social media platforms have emerged as powerful tools capable of shaping investor sentiment and, consequently, influencing market dynamics. While these platforms enhance access to information and promote market transparency, they also introduce challenges—particularly in the form of manipulative content that can mislead investors and undermine market efficiency.

Recent incidents—such as the influence of prominent individuals on asset prices through social media posts—have demonstrated how sentiment-driven narratives can shape financial decision-making. This development underscores the need for more robust analytical frameworks that move beyond traditional models, incorporating behavioral and sentiment-based approaches to better capture contemporary investment dynamics. In particular, platforms like Twitter have become valuable tools for gauging investor sentiment and identifying potential market manipulation. This study focuses on examining the effects of social media-driven sentiment on financial markets, with a specific emphasis on the NASDAQ Composite Index. By integrating Twitter-based sentiment analysis with econometric modeling, the research aims to determine whether manipulative activity on digital platforms has significant short- and long-term effects on market performance. In doing so, it contributes to the expanding literature on digital finance by providing empirical insights into the evolving interplay between online sentiment and financial market outcomes.

In conclusion, this study contributes to the existing body of literature by providing empirical insights into the relationship between Twitter sentiment and the NASDAQ Composite Index—an increasingly relevant connection for understanding investor behavior in the age of social media-driven financial markets.

2. LITERATURE SEARCH

Sentiment analysis, a subfield of Natural Language Processing (NLP), involves the computational assessment of human opinions and emotions expressed in written text. This technique has wide-ranging applications across various domains, including corporate marketing and sales, healthcare systems, and financial market analysis (Cristescu et al., 2022, p. 36).

The dynamic and complex nature of financial markets has challenged traditional analytical methods and opened new avenues for research. In recent years, the rapid growth of social media and digital transformation has elevated sentiment analysis in financial markets to a prominent research topic. Sentiment analysis involves examining the meaningful relationships between emotional and reactive data derived from big data sources—such as social media platforms—and financial asset prices and market movements.

Communication trends within communities are undergoing a significant transformation, as traditional communication mediums are increasingly being replaced by digital content and social media platforms. National boundaries are becoming less distinct, facilitating a more interconnected flow of information. Research in this area plays a crucial role in understanding investor behavior in financial markets and in predicting price movements. News, comments, emotional reactions, and trends shared on social media serve as valuable sources for assessing their impact on financial asset prices. The application of sentiment analysis in financial markets offers market participants the ability to respond swiftly, update risk management strategies, and enhance decision-making processes.

The studies that attempt to explain the role of social media sentiment analysis in financial markets are as follows:

With evolving communication modes, academic studies examining the relationships between financial trends and social media reactions have gained considerable attention. Zhang et al. (2011) conducted pioneering research predicting stock market indicators such as the DJIA, NASDAQ, and S&P 500 through Twitter sentiment analysis. They found that emotionally charged tweets negatively correlated with these indices but positively correlated with the VIX. By categorizing certain words as negative or positive (e.g., “fear” or “hope”), their analysis of tweets from 2006 to 2010 revealed that expressions of fear and concern were associated with declines in these indices. Rao and Srivastava (2012) demonstrated the superior performance of Twitter sentiment analysis compared to traditional methods in forecasting market movements for major indices like the DJIA and NASDAQ-100. Analyzing sentiments from millions of tweets related to these indices and large-cap technology stocks between June 2010 and July 2011, they reported a high correlation—up to 0.88 for returns—between stock prices and Twitter sentiments. Their research underscores the significant impact of public sentiment on short-term market performance. Katsafados et al. (2023) employed Panel VAR and ARDL models to analyze the relationship between social media sentiment scores and financial variables including BEL-20, DAX-30, CAC40, FTSE-MIB, IBEX-35, FTSE, and S&P 500. Utilizing the VADER model for sentiment analysis, their findings suggest that positive sentiment is linked to short-term increases in stock prices, with positive emotions correlating with high returns and low volatility in the short term. Conversely, in English-speaking countries, an increase in negative emotions is inversely related to stock prices and exerts a long-term effect. Negative emotions are also associated with lower returns in the short term. Renault (2017) provides a comprehensive analysis of how small-cap fraudsters exploit Twitter by disseminating false or misleading stock information to artificially inflate prices, effectively orchestrating pump-and-dump schemes. Examining millions of tweets related to small-cap stocks, the study identifies patterns of suspicious sentiment spikes correlated with short-lived price surges. Renault emphasizes that, while social media can serve as a valuable informational tool, it also presents fertile ground for market manipulation, particularly affecting less transparent firms. Yang et al. (2024) critically assess the impact of aggregated Twitter sentiment on equity market efficiency. Utilizing high-frequency data, they measure efficiency through return autocorrelation and variance ratio metrics, finding that elevated social media sentiment on the previous day reduces market efficiency, evidenced by increased predictable returns and volatility. They attribute this to intensified herding behavior, whereby traders collectively react to Twitter sentiment, thereby impeding optimal price discovery. Adams et al. (2023) constructed a real-time Twitter Financial Sentiment Index (TFSI) and demonstrated its predictive utility across various financial domains, including equity returns, credit spreads, and monetary policy surprises. Their findings indicate that declines in the TFSI often precede unexpectedly restrictive policy announcements and reliably forecast next-day stock returns. This research underscores Twitter's capacity to capture broad financial sentiment, influencing both investor behavior and macroeconomic expectations.

The studies that employ econometric modeling using a machine learning approach are as follows:

Kolasani and Assaf (2020) investigated the effectiveness of using Twitter posts to predict stock prices. By training various models on the Sentiment140 Twitter dataset, they found that Support Vector Machines (SVM) achieved the best performance in sentiment analysis, with an accuracy of 0.83. Their study focused on tweets containing keywords such as "stock market," "stocktwits," and "AAPL" to predict the stock prices of Apple Inc. and the Dow Jones Industrial Average (DJIA). They also employed a Multilayer Perceptron Neural Network model, concluding that while predicting indices posed challenges, tweets played a significant role in forecasting stock market movements. Harguem et al. (2022) focused on the NASDAQ 100, utilizing Twitter data to predict stock prices of companies worldwide. Their methodology involved classifying user tweets into optimistic, harmful, and neutral sentiments using the SVM machine learning algorithm with different kernels. The study achieved a maximum accuracy of 92% with the linear kernel and emphasized the importance of sentiment analysis in understanding the correlation between social media sentiment and stock market trends. Gaies et al. (2021) analyzed the relationship between the BMI Sensitivity Index and Bitcoin (BTC) prices using monthly data from August 2011 to July 2020. Employing Autoregressive Distributed Lag (ARDL) and Nonlinear ARDL (NARDL) methods, they demonstrated that investors utilize the sensitivity index to predict BTC prices. The index also aids portfolio managers in determining short- and long-term investment strategies. In the broader literature, besides studies related to the NASDAQ, several other significant works employ similar analytical methods. For instance, Rajput et al. (2022) conducted a study using the Google Trends Sentiment Analysis Index, Bitcoin (BTC) prices, and USD exchange rate data from 2013 to 2018. They applied the ARDL method to investigate whether the Sentiment Analysis Index could predict BTC returns, trading volume, and volatility associated with BTC returns. Their findings indicated that the USD was negatively affected by BTC prices in both the short and long term. Furthermore, they highlighted the asymmetric effects of BTC sentiment on both BTC prices and fiat currency.

The other related econometric studies are as follows:

Chen (2022) examined the relationship between Bitcoin (BTC) prices, BTC mining data, and Google Trends data from February 7, 2016, to February 7, 2021, employing the Autoregressive Distributed Lag (ARDL) method. The study revealed that BTC prices responded more dramatically to changes in attitudes toward mining activities, especially after 2019, with the correlation between these variables strengthening over time. Gozbasi et al. (2021) analyzed monthly data from August 2010 to April 2021 to explore the relationship between BTC prices and the S&P 500 index. Using ARDL and Granger Causality tests, they found that BTC prices showed limited reaction to volatility in the commodity market, responding only to oil prices in the short term, while gold prices had no statistically significant effect on BTC prices. Furthermore, increases in crude oil prices negatively impacted BTC prices in the short term, with no significant long-term effect observed. Kjærland et al. (2018) investigated weekly data from September 8, 2011, to February 5, 2017, to understand the relationship between BTC prices, the S&P 500, and Google Trends. By employing ARDL and Least Squares methods, they discovered a significant and positive relationship between public interest in BTC—as measured by Google search volume—and BTC price fluctuations.

Collectively, these studies underscore the critical role of social media sentiment analysis in forecasting stock market trends. They demonstrate that emotions—both positive and negative—expressed on platforms like Twitter can exert significant short- and long-term effects on stock prices, highlighting social media as an increasingly influential external factor in financial decision-making. While prior research has employed various methodologies—such as ARDL models, machine learning algorithms, and sentiment indices—to explore the relationship between online sentiment and financial indicators, the majority focus on broad time horizons or general investor behavior.

This study differentiates itself by narrowing its focus to a highly specific and volatile timeframe, December 2021 to January 2022—a period marked by heightened uncertainty and substantial fluctuations in the NASDAQ Composite Index. By examining the short- and long-term impacts of potentially manipulative Twitter activity during this critical window, the study offers a time-sensitive and targeted contribution to the literature. Moreover, the integration of sentiment analysis with the ARDL bounds testing approach introduces a novel empirical framework for assessing whether sentiment-driven manipulation exerts statistically significant effects on market dynamics. In doing so, the study advances our understanding of investor behavior in the digital era and contributes meaningfully to the growing fields of behavioral finance and digital market efficiency. By focusing on a volatile and underexplored market phase, this research fills a notable gap in the literature and offers nuanced insights into the dynamic interplay between Twitter sentiment and the performance of the NASDAQ Composite Index.

3. DATA MINING AND SENSITIVITY ANALYSIS

Data mining is fundamentally the extraction of meaningful patterns from large datasets using methods such as classification, clustering, and association rule mining, and represents a crucial phase within the broader knowledge-discovery paradigm (Pruengkarn et al., 2017; Solomon, 2014). A significant advancement in this domain is the incorporation of sensitivity analysis—especially global sensitivity analysis (GSA), which evaluates how uncertainty in input variables affects model outputs across their full distribution, quantifying input relevance via methods such as variance-based Sobol indices and screening tools like Morris's method (Iooss & Lemaître, 2015; Saltelli et al., 2008). Recent literature demonstrates that GSA is beneficial in enhancing model interpretability and robustness within data mining workflows: for example, it has been utilized to identify influential pixel regions in neural network classifiers for MNIST digits and to benchmark different GSA techniques in feature-selection contexts (Sadeghi & Matwin, 2024; Yao, 2003). Integrating sensitivity analysis into data mining pipelines therefore supports a dual objective—not only revealing significant structural patterns but also quantifying the drivers of model behavior under uncertainty, which enables more transparent and dependable decision-making.

Sentiment analysis has become increasingly important for swiftly interpreting the growing volume of opinions shared on social media and other digital platforms. In recent years, the exponential rise in communication channels, digital content, air traffic, and alternative markets has generated an overwhelming amount of data—rendering traditional analytical methods insufficient. In response, researchers have developed high-efficiency techniques to process and analyze this information effectively. Sentiment analysis aims to accurately identify the polarity of textual data—positive, negative, or neutral—to support informed decision-making. The process typically involves five key steps: data collection, text preprocessing, sentiment detection, sentiment classification, and output presentation (Aqlan et al., 2019, p. 149). Sentiment modeling can be approached in three primary ways: dictionary-based models, machine learning models, and hybrid models. In this study, a dictionary-based model—TextBlob—is employed. TextBlob is a natural language processing (NLP) library in Python that simplifies textual data analysis, including sentiment detection. For the sentiment analysis conducted in this research, Python is used in conjunction with TextBlob. Underlying TextBlob is the Natural Language Toolkit (NLTK), an open-source NLP library that supports various tasks such as text classification, tokenization, part-of-speech tagging, parsing, stemming, and sentiment analysis (Natural Language Toolkit [NLTK], 2023).

Sensitivity analysis is presented as a time series and is assigned a value between -1 and +1 for the desired day, month, week, or year. When the obtained value approaches -1, it indicates a negative sentiment about the researched parameter, while approaching +1 signifies positive sentiments about the respective parameter.

In order to access sensitivity analysis, daily data was initially collected. For sensitivity analysis, the most liked 50 English tweets, using the NASDAQ hashtag, posted on Twitter between 01.12.2021 and 31.01.2022 were retrieved through the APIFY platform. Since the tweets between these dates couldn't be obtained using a Twitter developer account, they were collected from the internet using the

"Twitter URL Scraper" module within the APIFY application. The obtained tweets were daily converted into text documents and analyzed as a single daily text.

To perform sensitivity analysis, after obtaining the data, the text was prepared for analysis. The following steps were followed during the text cleaning process:

- Converting uppercase letters to lowercase: Uppercase letters in the text were converted to lowercase to ensure consistency in the analysis and facilitate data processing.
- Removing non-English words: Non-English words in the text were removed because they could introduce unwanted noise during the analysis.
- Removing unnecessary words in the stopword list: Using a list known as a stopword list, which contains unimportant or meaningless words for text analysis, such words were removed from the text.
- Removing numbers: Numerical values in the text were removed as they were not necessary for sensitivity analysis.
- Removing special characters: Special characters in the text were removed to avoid unwanted effects on the analysis.
- Removing emoticons and emojis: Emoticons and emojis in the text were removed as they were not suitable for sensitivity analysis.
- Extracting single-word expressions: Expressions consisting of only a single word were removed from the text, as they were considered to contain insufficient information for analysis.
- Cleaning 'url' extensions indicating internet links: Internet links in the text were removed because they did not contribute to the content to be used in sensitivity analysis.
- Removing user names: User names in the text were removed as they did not contain important information for the analysis.
- Removing punctuation marks: Punctuation marks in the text were removed because they could introduce unnecessary noise during the analysis.
- Removing the NASDAQ hashtag: The NASDAQ hashtag in the text was removed as it was not suitable for the analysis purpose. After preparing the text for analysis and downloading the necessary Python libraries, sensitivity analysis results were obtained using the code created by us.

To contribute to the evaluation of the results, word frequency clouds were created from the cleaned text to visualize word frequency. The wordcloud library was used to create the word cloud, and it was visualized using the matplotlib library.

Figure 1. Word Clouds

Note: Left: Word cloud extracted from the given time period. Right: Word cloud that occurred on the last date of the index decline.

As shown in the left-hand figure, the word cloud generated from tweets containing the NASDAQ hashtag between December 1, 2021, and January 31, 2022, visually represents the most frequently used terms during this period. The size of each word indicates its frequency and relative prominence. Common terms include “market,” “stock,” “today,” “time,” “new,” and “day,” reflecting general discussions surrounding financial activities.

Understanding the sentiment surrounding the NASDAQ stock exchange is essential, and the word cloud should be interpreted in conjunction with the accompanying trend graph. The overall sentiment trajectory, as illustrated by the trend graph, appears predominantly positive throughout the broader time frame. However, the right-hand figure—depicting the word cloud from January 31, 2022, the date marking a notable decline—demonstrates a clear shift in tone. Terms such as “warning,” “worst,” and “fallen” signal a strong negative emotional response. This change is also reflected in the sentiment trend graph, which shows a distinct downturn, validating the alignment between textual sentiment and market developments.

This study adopts a mixed-methods approach by integrating Twitter Sentiment Analysis (TSA) with the Autoregressive Distributed Lag (ARDL) model to investigate the impact of social media sentiment on financial markets comprehensively. The justification for employing sentiment analysis lies in its capacity to capture the behavioral and psychological dimensions of investor activity, especially within the context of social media. Twitter, as a widely utilized platform for financial discourse and speculation, offers a rich source of real-time sentiment data. TSA facilitates the quantification of investor mood, serving as a behavioral proxy in financial decision-making.

The ARDL model, in turn, was selected due to its ability to estimate both short- and long-run relationships between variables, even when the variables are integrated at different levels. In this study, stationarity tests—including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Fourier ADF (FADF)—confirmed that the TSA series is stationary at level I(0), while the NASDAQ Composite Index is integrated at first difference, I(1). The ARDL bounds testing approach is particularly suitable for such data characteristics, enabling robust analysis without the need for pre-testing for cointegration.

By combining TSA with the ARDL framework, this study bridges the gap between behavioral finance and traditional econometric modeling. TSA provides a dynamic and timely measure of investor sentiment, whereas ARDL captures the causal impact of that sentiment on market movements over different time horizons. This integrated methodology enhances the explanatory power of the research and contributes to a deeper understanding of the complex interplay between investor psychology and financial market dynamics in the digital age.

4. ECONOMETRIC MODELING

When working with financial time series, ensuring stationarity is of paramount importance. In this study, both structural break-sensitive and structural break-insensitive unit root tests were employed to establish the stationarity of the series. The following unit root tests were used:

1. The Phillips-Perron Unit Root Test: Developed by Phillips and Perron in 1988, the Phillips-Perron Unit Root Test, also known as the PP test, ensures stationarity without allowing for structural breaks (Phillips & Perron, 1988).

2. The Augmented Dickey Fuller Unit Root Test: Another commonly used test for determining stationarity, the Augmented Dickey Fuller (ADF) Unit Root Test, was developed by Dickey and Fuller (1981).

3. The Flexible Fourier Form Dickey-Fuller Unit Root Test (FADF): Allowing for structural breaks, the FADF, also known as The Flexible Fourier Form Dickey-Fuller Unit Root Test, was developed by Enders and Lee (2012).

Following the unit root tests, an additional analysis was conducted using the Autoregressive Distributed Lag Bounds Test (ARDL), also known as the ARDL model, developed by Pesaran et al. (2021). The results were discussed in both the short and long terms.

4.1. Dataset and Methodology

Numerous studies have been conducted on time series data, and the approaches to studying the parameters of a series vary. In this study, the variables used are the NASDAQ index and sentiment analysis values of tweets posted with the NASDAQ hashtag. The table below shows the variables and their sources used in the study:

Table 2. Variables and Sources

Variables	Explanations	Sources
NASDAQ Composite Index	IXIC	Investing
TSA	Sentiment Analysis Results of the 50 Most Popular Daily Tweets Posted with the NASDAQ Hashtag	Twitter, APIFY

The descriptive statistics of the variables under analysis are displayed in the following table:

Table 3. Descriptive Statistics

	TSA	NASDAQ
Mean	0.089378	15,031.61
Median	0.099647	15,198.89
Maximum	0.335714	15,895.20
Minimum	-0.214286	13,436.71
Std. Dev.	0.101074	714.5402
Skewness	-0.192790	-0.953296
Kurtosis	4.063246	2.807186
Jarque-Bera	3.304506	9.486703
Probability	0.191618	0.008709
Obs.	62	62

Table 3 provides descriptive statistics for the Twitter Sentiment Analysis (TSA) variable and the NASDAQ index based on 62 observations. The mean value of TSA is 0.0894, indicating a slight predominance of positive sentiment, while the NASDAQ index has a considerably higher mean of 15,031.61, reflecting its scale. TSA exhibits lower volatility with a standard deviation of 0.1011 compared to 714.54 for NASDAQ. Both variables are negatively skewed, with TSA (-0.1928) being closer to symmetry than NASDAQ (-0.9533). The kurtosis values suggest that TSA (4.0632) is more leptokurtic than NASDAQ (2.8072), implying heavier tails in its distribution. The Jarque-Bera test statistic further reveals that TSA does not significantly deviate from normality (JB = 3.3045, p = 0.1916), whereas NASDAQ shows a statistically significant departure (JB = 9.4867, p = 0.0087). Overall, TSA displays more stable and near-normal distributional characteristics compared to the NASDAQ index.

Following the descriptive statistics, the correlation matrix between variables is displayed in Table 4.

Table 4. Correlation Matrix between TSA and NASDAQ

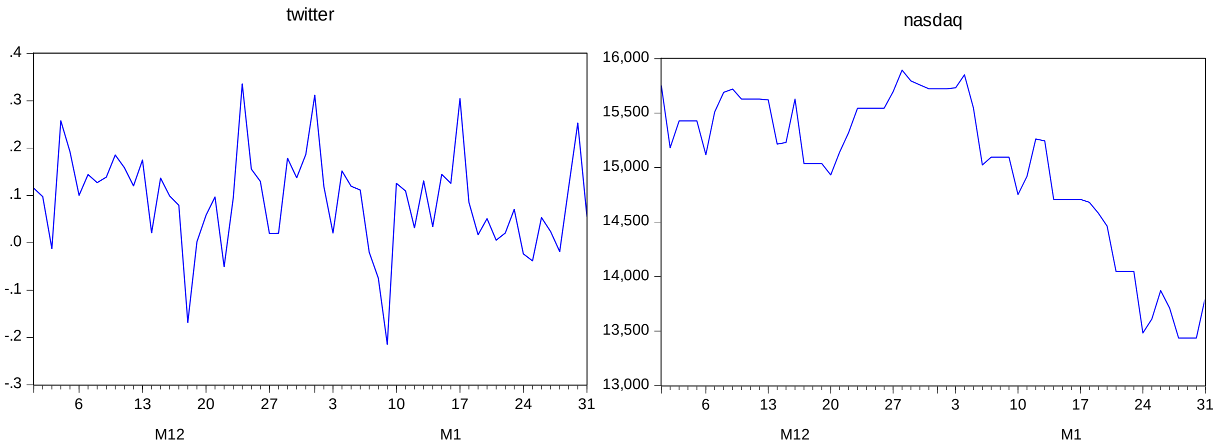
	TSA	NASDAQ
TSA	1.000000	

NASDAQ	0.274013	1.000000
Prob.	0.0312	-----

As can be seen, there is a statistically significant positive relationship between NASDAQ and TSA at a 5% significance level. Despite the coefficient being positive, its value of 0.27 (closer to 0) indicates that the relationship is weak.

Before conducting unit root tests, the trend charts of the variables within the selected period are as shown in the following figures:

Figure 2. TSA and NASDAQ Trend Charts



As can be observed from the figures, the TSA variable has shown a fluctuating trend over time. When examining the trend graph of the NASDAQ index over the selected time period, it is observed that it provided a stable return in the mid-term. However, a decline is noted after the mid-term period.

4.2. Results of Unit Root Tests Allowing and Not Allowing Structural Breaks

Stationarity plays a critical role in time series analysis, as the direction and methodology of the study are largely determined by the outcomes of stationarity tests. In the initial stage of this research, traditional unit root tests that do not account for structural breaks were employed. Specifically, the Augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller (1979), and the Phillips-Perron (PP) test, introduced by Phillips and Perron (1988), were utilized to examine the stationarity properties of the variables. The test results for the NASDAQ variable are presented in Table 5.

Table 5. Traditional Unit Root Test Results for NASDAQ and TSA

PHILLIPS PERRON UNIT ROOT TEST			
	At level		
		LOGNASDAQ	TSA
Constant	t-Statistic	-0.6730	-5.6847
	Probability	*0.8454*	*0.0000****
Constantand Trend	t-Statistic	-1.7143	-5.7806
	Probability	*0.7329*	*0.0001****
None	t-Statistic	-1.3484	-3.7953
	Probability	*0.1628*	*0.0003****
	1st difference		
		d(LOGNASDAQ)	d(TSA)
Constant	t-Statistic	-8.5601	-34.0204
	Probability	*0.0000****	*0.0001****
Constant and Trend	t-Statistic	-9.0335	-33.9515
	Probability	*0.0000****	*0.0001****
None	t-Statistic	-8.5266	-34.5248
	Probability	*0.0000****	*0.0000****
AUGMENTED DICKEY-FULLER UNIT ROOT TEST			
	At level		
		LOGNASDAQ	TSA
Constant	t-Statistic	-0.8630	-5.6689
	Probability	*0.7934*	*0.0000****
Constant and Trend	t-Statistic	-1.9271	-5.8056
	Probability	*0.6283*	*0.0000****
None	t-Statistic	-1.0747	-3.8911
	Probability	*0.2526*	*0.0002****
	1st difference		
		d(LOGNASDAQ)	d(TSA)
Constant	t-Statistic	-7.2613	-8.5462
	Probability	*0.0000****	*0.0000****
Constant and Trend	t-Statistic	-7.4185	-8.4559
	Probability	*0.0000****	*0.0000****
None	t-Statistic	-7.0517	-8.6188
	Probability	*0.0000****	*0.0000****

Note: *, **, *** respectively represent significance levels of 10%, 5%, and 1%.

The traditional unit root tests conducted on the NASDAQ series indicate that the variable is non-stationary at level. However, upon taking the first difference, the series becomes stationary at the 1% significance level according to both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The results of the same unit root tests applied to the Twitter Sentiment Analysis (TSA) variable are presented in Table 5.

When examining the results of unit root tests applied to TSA, it is noticeable that the series achieves stationarity in level values. However, to ensure the robustness of unit root tests, it was decided to apply the FADF test developed by Enders and Lee (2012), which belongs to the modern school of thought and allows for structural breaks.

As known, for the FADF test to be valid, certain conditions must be met. Firstly, a new model is constructed by taking the first differences of the series.

Table 6. FADF Unit Root Test Results

Series	Min. KKT	*k*	FADF
NASDAQ	2,858,952	1	3.353617 (2)
TSA	0.505567	3	3.554876 (-)

Note: *, **, *** respectively indicate significance at the 10%, 5%, and 1% levels. The values in parentheses are the optimal lag lengths.

Here, the "k" values are used to determine the "total sum of squares" and to find the appropriate frequency range. This formulation, established in the EViews 10 program, resulted in finding different frequencies of suitability for the two series. The optimal frequency range for NASDAQ index was found to be "1", while for TSA, it was found to be "5". Another essential assumption of FADF is to calculate the appropriate lag length after determining the frequency range.

In the Augmented Dickey-Fuller (ADF) or Flexible ADF (FADF) unit root test, the appropriate lag length is crucial to ensure that the error term is white noise. The test regression includes lagged differences of the dependent variable to address serial correlation, and the optimal number of lags (p) can be determined using various information criteria. Commonly employed criteria include the Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SIC/BIC), and the Hannan-Quinn Criterion (HQ), each minimizing a function that penalizes the residual variance based on the number of estimated parameters and sample size. The formulas for these criteria are:

$$AIC(p) = \ln(\sigma^2) + \frac{2k}{T}$$

$$BIC(p) \; = \; ln(\sigma^2) \; + \; k \cdot ln(T)/T$$

and

$$HQ(p) \; = \; ln(\sigma^2) \; + \; 2k \cdot ln(ln(T))/T$$

where σ^2 denotes the estimated variance of residuals, k is the number of parameters, and T is the sample size (Lütkepohl, 2005).

In our study, lag length could not be calculated for any value. It is stated that the ADF unit root test results are valid because the series does not meet the FADF assumptions. According to these results, NASDAQ is stationary at I(1), and TSA is stationary at I(0).

The presence of stationarity at different orders of integration is essential for econometric modeling. Therefore, since the series exhibit stationarity at varying integration levels, the application of the ARDL model is considered appropriate for this study.

4.3. Application of the ARDL Model to the Time Series Data

The ARDL boundary test developed by Pesaran et al. (2001) is a commonly used analytical model in time series analysis, particularly when there are different levels of stationarity. The purpose of establishing the model is to determine the presence or absence of a cointegration relationship among the series. If cointegration exists, short and long-term coefficients of the series are estimated.

The model we have established meets all the requirements of the ARDL boundary test. The Akaike information criterion was selected, and the coefficient of the covariance matrix, as well as the problem of changing variance and autocorrelation, were addressed using the Heteroskedasticity and Autocorrelation Consistent Covariance (HAC) estimators developed by Newey and West (1987). The appropriate lag order for building the ARDL model was determined to be 1 shown at table 7, based on the Akaike information criterion.

Table 7. Lag Length Criteria for Bound Test

Lag	LogL	LR	FPE	AIC	SC	HQ
0	142.7996	NA	2.45e-05	-4.940338	-4.868652	-4.912478
1	212.2755	131.6384*	2.47e-06*	-7.237735*	-7.022677*	-7.154157*
2	213.3711	1.999152	2.73e-06	-7.135830	-6.777400	-6.996532
3	216.5349	5.550357	2.82e-06	-7.106486	-6.604684	-6.911469
4	221.5574	8.459079	2.73e-06	-7.142366	-6.497192	-6.891629
5	225.4439	6.272868	2.75e-06	-7.138382	-6.349836	-6.831926

According to the model established in the E-Views 10 program, the suitable model is estimated as ARDL(1,0). The table below shows the F-statistic value and criteria found for the ARDL(1,0) model.

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta\lambda_t + \varepsilon_t$$

$$NASDAQ_t = \alpha_0 + \mathrm{NASDAQ}_{t-1} + \beta \mathrm{TSA}_t + \varepsilon_t$$

For the bounds testing procedure, the following hypotheses are tested to determine the existence of a long-term relationship:

H_0 : $\alpha_1 = \beta = 0$ (There is no relationship among the variables)

H_1 : $\alpha_1 \neq \beta \neq 0$ (There is a relationship among the variables)

Table 8. ARDL(1,0) F-Statistic and Critical Values

Model	k	M	F-Statistic	Significance Level	Lower Bound	Upper Bound
ARDL(1,0)	1	4	17.8153***	%10	4.175	4.93
				%5	5.13	5.98
				%1	7.32	8.435

Note: M represents the maximum number of lags, k denotes the number of explanatory variables, and *** signifies the 1% significance level.

The critical values used for the lower and upper bounds were taken from Table CI(ii) in the study conducted by Pesaran et al. (2001, p. 300). As can be seen from the table, the F-statistic value of the model is 17.81, which exceeds both the lower and upper bounds of the critical values at the 10%, 5%, and 1% significance levels. The model is found to be statistically significant at the 1% level. This indicates the presence of a cointegration relationship between the dependent and independent variables. Based on these results, the null hypothesis (H_0) is rejected, and the alternative hypothesis (H_1) is accepted. However, it is essential to validate the hypothesis through appropriate diagnostic tests to ensure the robustness and reliability of the model.

Table 9. Diagnostic Tests

Breusch-Godfrey Serial Correlation LM Test	0.406357 (0.6464)
Normality Test	3.608000 (0.164639)
Heteroskedasticity Test: Breusch-Pagan-Godfrey Test	0.814114 (0.4348)
Ramsey RESET Test	0.420381 (0.5194)

Note: The values in parentheses represent the probability (p) values of the diagnostic tests.

The probability (p) values exceeding 0.05 indicate that there is no statistically significant issue with the specification of the model.

The Breusch-Godfrey Serial Correlation LM Test yielded a test statistic of 0.406357 with a corresponding p-value of 0.6464. Since the p-value exceeds conventional significance levels (e.g., 0.05), the null hypothesis of no serial correlation cannot be rejected, indicating that the residuals do not exhibit autocorrelation.

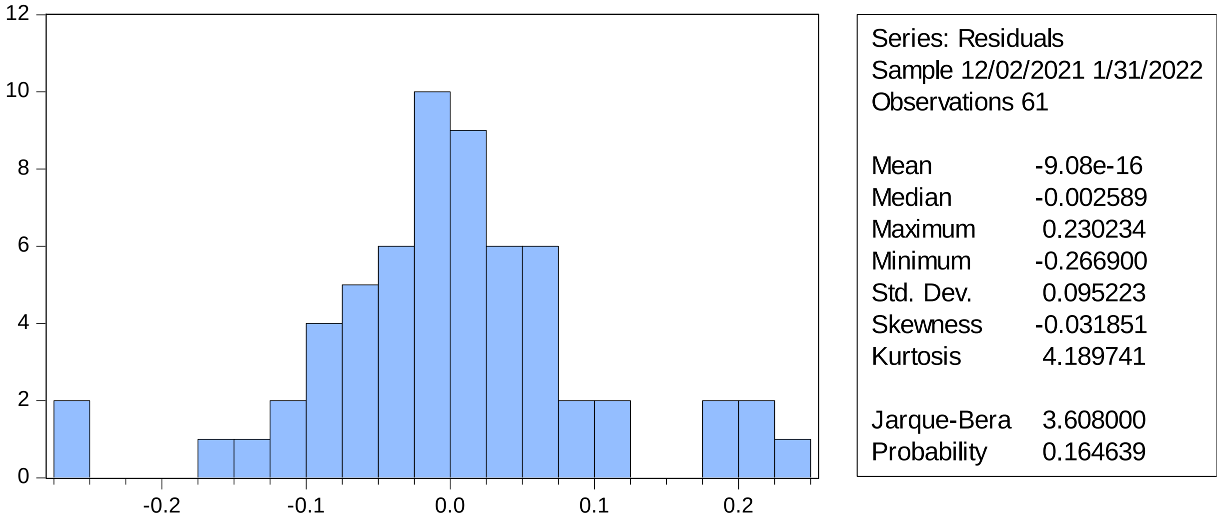
The Normality Test (Jarque-Bera) produced a test statistic of 3.608000 and a p-value of 0.164639. As the p-value is greater than 0.05, the null hypothesis of normally distributed residuals is not rejected, supporting the assumption of normality in the model's error terms.

The Breusch-Pagan-Godfrey Test for heteroskedasticity returned a test statistic of 0.814114 with a p-value of 0.4348. This result suggests that the null hypothesis of homoskedasticity cannot be rejected, indicating constant variance in the residuals and the absence of heteroskedasticity.

Finally, the Ramsey RESET Test statistic is 0.420381 with a p-value of 0.5194. Since the p-value is well above the 0.05 threshold, the null hypothesis that the model is correctly specified cannot be rejected, implying that the functional form of the model is appropriate.

The significant F-statistic allows for the interpretation of coefficients for both short and long-term relationships after confirming the assumptions of the ARDL model. The absence of autocorrelation, model specification error, and changing variance issues is essential for interpreting these coefficients in the model. In the autocorrelation test, the probability value is found to be 0.94, which is greater than 0.01, suggesting the absence of an autocorrelation problem. The result of the normality test applied to the model is as follows:

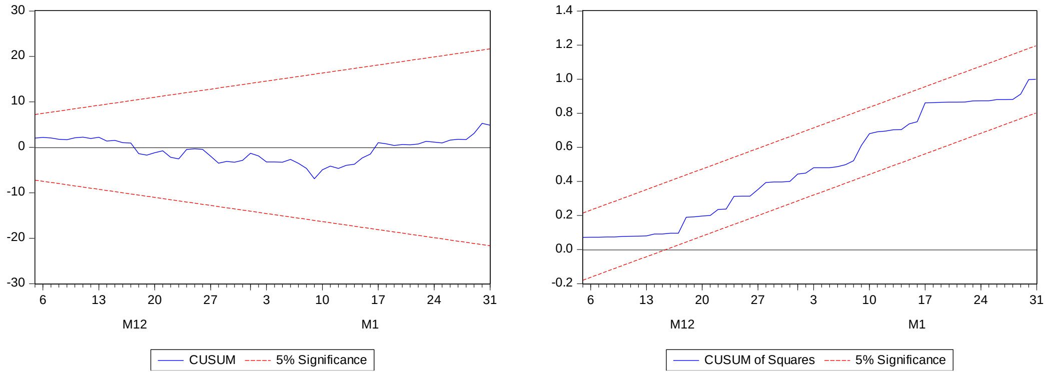
Figure 3. Normality Test of the ARDL Model



In the normality assumption, the probability value (0.16) is greater than 0.01, confirming the normality assumption. The histogram of residuals illustrates the distribution of the error terms from the model over the sample period spanning from December 2, 2021, to January 31, 2022, comprising 61 observations. The residuals exhibit a near-symmetric distribution with a mean value effectively equal to zero (mean = -9.08e-16), indicating an unbiased estimation. The median residual is slightly negative at -0.002589, reinforcing the central tendency close to zero. The spread of the residuals is moderate, with a standard deviation of 0.095223, and the residuals range between a minimum of -0.266900 and a maximum of 0.230234. Skewness is minimal at -0.031851, suggesting a near-symmetric distribution of residuals without significant asymmetry. However, the kurtosis value of 4.189741 indicates a leptokurtic distribution, implying a slightly heavier tail compared to the normal distribution. The Jarque-Bera test statistic is 3.608 with an associated p-value of 0.164639, which exceeds conventional significance thresholds (e.g., 0.05). Consequently, the null hypothesis of normality cannot be rejected, supporting the assumption that residuals are normally distributed. Overall, the residual diagnostics suggest that the model residuals meet the assumptions of unbiasedness, homoscedasticity, and approximate normality, reinforcing the adequacy of the model specification for the analyzed sample period.

As seen, three assumptions of the ARDL test have been tested, and there are no issues found for model establishment. However, to enhance reliability and to determine whether there is a structural break in the model, the CUSUM test developed by Brown et al. (1975) has been applied, and the results are as shown in the following figure:

Figure 4. CUSUM and CUSUM of Square Chart



According to the CUSUM and CUSUM of Squares test, the coefficients move within the critical values, indicating the absence of structural breaks. Therefore, no dummy variable is required.

Once the ARDL assumptions are met, the long and short-term coefficients of the model can be interpreted. The tables below show the long and short-term coefficients of the NASDAQ and TSA series:

Table 10. ARDL Long-Term Coefficients

Variables	Co-eff.	Standard Error	t-Statistic	Prob.
LOGNASDAQ	0.566055	0.315371	1.794888	0.0779
C	-4.084255	2.564396	-1.592677	0.1167

When examining the probability values in the long term, the coefficient for NASDAQ is statistically significant at the 10% significance level. However, the coefficient has a positive sign, indicating that the impact of NASDAQ prices on TSA is positive. The probability value of the long-term coefficient falling between 5% and 10% is significant for the series' validity. However, a positive coefficient can always be interpreted. The coefficient of LOGNASDAQ is estimated at 0.566, with a standard error of 0.315. The corresponding t-statistic is 1.79, indicating marginal statistical significance at the 10% level ($p = 0.0779$). This suggests that a one-unit increase in the logarithm of the NASDAQ index is associated with an approximate 0.566 unit increase in the dependent variable, although the evidence is not strong enough to confirm this relationship at conventional 5% significance levels. The formula for the established long-term relationship is as follows:

TSA = (0.5661*LOGNASDAQ)

Table 11. ARDL Short-Term Coefficients

Variables	Co-eff.	Standard Error	t-Statistic	Prob.
C	-4.084255	0.678353	-6.020842	0.0000***
ECT_{t-1}	-0.762766	0.126697	-6.020375	0.0000***

Not: *, **, *** respectively indicate significance at the 10%, 5%, and 1% levels, and ECTt-1 represents the "Error Correction Term."

The functioning of the error correction term has significant importance for the model. For the error correction term to function correctly, its coefficient should have a negative sign and its probability value should be significant at 0.01. In the established model, the coefficient is -0.76, and the probability value is 0.00. Therefore, the model is considered to be correct.

The Error Correction Term (ECT) indicates whether the deviations in the dependent variable caused by past data are corrected by the independent variable in the long run. In other words, it shows whether the independent variable has a long-term effect on restoring equilibrium following shocks that lead to deviations from the mean in the dependent variable. The magnitude of the ECT coefficient reflects the strength of the error correction mechanism. When looking at the coefficient of the error correction term, it indicates that any long-term deviation between the variables is corrected by 76% in the following period. It can be interpreted that the gap is closed in the next period.

The R-squared value indicates the explanatory power of the model. The adjusted R-squared value reveals that 37% of the variation in TSA is explained. Considering the probability value of the F-statistic, which is less than 0.01, the model is deemed significant.

5. CONCLUSION AND DISCUSSIONS

Within the framework of the ARDL model, the roles of the dependent and independent variables were reversed in the study. Since the Twitter Sentiment Analysis results were found to have no significant effect on the NASDAQ index in both the long and short term, this finding was not reported.

This study examined the presence of both long- and short-term relationships between TSA and NASDAQ trends. The econometric analyses indicated that while the coefficients were not significant in the long term, a positive relationship was found in the short term. To determine the direction of this relationship, the roles of the dependent and independent variables were reversed. When NASDAQ was the dependent variable and TSA the independent variable, no significant relationship was detected. This implies that tweets containing the NASDAQ hashtag may not directly influence NASDAQ trends, either positively or negatively. However, when TSA was the dependent variable and NASDAQ the independent variable, it was observed that changes in the NASDAQ index affected Twitter activity in the short term. This suggests that Twitter activity referencing NASDAQ does not directly impact NASDAQ index movements. Conversely, in this second model, significant relationships were identified. The error correction term was significant in the short term, indicating a robust model fit, and a 1% increase in the NASDAQ index corresponded to a 0.56% increase in Twitter popularity in the long term.

These results imply that changes in the NASDAQ index influence Twitter discussions related to NASDAQ, particularly over longer periods. These findings are consistent with existing literature highlighting the impact of market movements on social media sentiment (Harguem et al., 2022), while challenging studies that posit the reverse causality from Twitter sentiment to market performance (Rao & Srivastava, 2012; Zhang et al., 2011). Our results emphasize the importance of considering the directionality of influence when analyzing social media and financial market interactions.

The literature contains studies on stock indices and sentiment analyses, primarily focusing on investor behavior. Similar to the findings of Harguem et al. (2022), this study underscores the influence of market movements on social media sentiment, reinforcing the interconnectedness between financial indices and social media activities. However, this study adds a different dimension by changing the dependent variable. Consequently, it was found that the NASDAQ Twitter popularity does not affect the index price in the short or long term. However, it was determined that changes in the index price influence Twitter activity. This finding challenges the assumptions of Zhang et al. (2011), who found emotional tweets correlated with stock indices, and by Rao and Srivastava (2012), who highlighted the impact of Twitter sentiments on market performance. Our findings accept the relation between TSA and NASDAQ index but the independent variable should be NASDAQ. Kolasani and Assaf (2020) specifically analyzed the movements of certain technology stocks. The relationship between Twitter activity and stock prices may vary across different sectors. However, Kolasani and Assaf's work is significant for evaluating the performance of the SVM model in NLP studies. In our study, the focus on NASDAQ stocks resulted in different findings. In these aspects, the study diverges from the existing literature and is open to further development.

Based on the findings of this study, which indicate that Twitter sentiment does not exert a significant long- or short-term influence on NASDAQ index pricing, but rather is itself shaped by fluctuations in the index, several policy implications emerge. Regulators and market participants should reconsider the presumed causality between social media sentiment and financial market performance. Efforts aimed at monitoring or controlling market volatility through sentiment analysis may yield limited effectiveness if sentiment primarily reacts to, rather than drives, market movements. Therefore, instead of allocating extensive resources to sentiment-based forecasting models for stock indices, attention should be directed towards enhancing investor education and transparency in financial communications. Furthermore, platforms like Twitter could be encouraged to improve the contextual labeling of financial content to help users better interpret emotionally charged or reactive posts that emerge during periods of heightened market activity. The relationship between investor sentiment and stock market indices, as explored in this study, can be effectively framed within the broader context of behavioral finance and the Efficient Market Hypothesis (EMH). While EMH assumes that asset prices fully reflect all available information, behavioral finance highlights systematic biases and irrational behavior that may cause deviations from fundamental values. The influence of social media sentiment, particularly manipulative or emotionally charged content, represents a behavioral anomaly that challenges the assumptions of market efficiency. By incorporating Twitter-based sentiment analysis into an ARDL framework, this study contributes to the understanding of how psychological factors and information dissemination through digital platforms can affect price formation and market dynamics. Thus, the findings offer empirical support to behavioral finance theories, suggesting that in certain periods—especially during market corrections—investor sentiment significantly impacts index performance, potentially leading to temporary inefficiencies in the market. If a single conclusion is to be drawn from this study, it is that investors should avoid making decisions based solely on social media manipulations and instead engage in comprehensive and evidence-based analyses. Relying on rigorous research rather than sentiment-driven content can lead to more rational and informed investment strategies.

Ethics Committee approval was not required for this study.

The author declares that the study was conducted in accordance with research and publication ethics.

The author confirms that no part of the study was generated, either wholly or in part, using Artificial Intelligence (AI) tools.

The author declares that there are no financial conflicts of interest involving any institution, organization, or individual associated with this article.

The author affirms that the entire research process was performed by the sole declared author of the study.

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