International Journal of
Economics Development Research, Volume 6(6), 2025
pp. 3106-3129

Post-Event Analysis of The Influence of President Donald Trump's Tweet Sentiment on the Abnormal Return, Trading Volume Activity, and Volatility of S&P 500 Companies

Muhammad Angga Farizki Ar Rasyid [1]

Abstract:

This study examines the impact of tweet sentiment—both positive and negative—and its effect on the day the tweet is posted (event day) and the following day (post-event day) on abnormal return, trading volume activity, and volatility of companies listed on the Standard & Poor's 500 stock exchange that were directly mentioned in President Donald Trump's tweets between 2016 and 2019. Using panel data consisting of 326 time series observations and 29 company units, the results indicate a significant positive influence of sentiment on volatility, where positive sentiment tends to reduce market uncertainty. Additionally, there is a delayed effect of time on abnormal return, suggesting that the market responds slowly to information received. These findings support the semi-strong form of the Efficient Market Hypothesis, which posits that investors are capable of processing public information selectively but not operate full alignment when making decisions in the stock market.

Keywords: *Sentiment Tweet, Abnormal Return, Trading Volume Activity, Volatility, S&P500*

Submitted: July 22, 2025, Accepted: September 28, 2025, Published: October 10, 2025

1. Introduction

Social media platforms have evolved from mere entertainment tools into influential channels for marketing and real-time information exchange, warranting critical analysis of their market impact (Ajjoub, Walker, and Zhao 2021). As misinformation concerns rise—with 42% of Americans attributing viral fake news to these platforms (Barthel, Pew Research Center)—Twitter has emerged as a central node in investor decision-making. Once the 10th most visited website globally, Twitter serves diverse functions including financial analytics (FANG and PERESS 2009; Qiu, Rui, and Whinston 2013), and is increasingly recognized for its predictive relevance in stock market dynamics. Studies reveal that 97% of institutional investors use digital media for information, with 79% leveraging social media in professional settings and 40% believing it enhances annual performance (Connell 2015). Posts from figures like Donald Trump, whose tweets often targeted public companies, exemplify social media's capacity to provoke measurable market responses (Gjerstad et al. 2021).

Although formal academic research in this area remains limited, scholarly and media interest in the impact of social media—particularly Twitter—on financial markets has

[1] *Universitas Negeri Surabaya, muhammad.21120@mhs.unesa.ac.id.*

grown considerably (Ajjoub, Walker, and Zhao 2021). For instance, Amazon's stock experienced a significant decline following a negative tweet by President Donald Trump (Deagon 2018), while Toyota reportedly lost nearly USD 1.8 billion in value after being directly criticized by Trump on Twitter (Revesz 2017). The Los Angeles Times observed that traders began analyzing Trump's tweets algorithmically and made near-instantaneous trading decisions based on their content (Peltz, 2017). Similarly, Time Magazine reported a sharp depreciation of the U.S. dollar after Trump tweeted that it was "too strong" (Abramson 2017). These examples highlight the profound market influence of a single tweet, especially when the tweet coincides with ongoing financial news. In fact, research suggests that Trump's online presence may exert greater influence than traditional financial media, with the effect of his tweets being amplified when paired with relevant news coverage(Yuan et al. 2020).

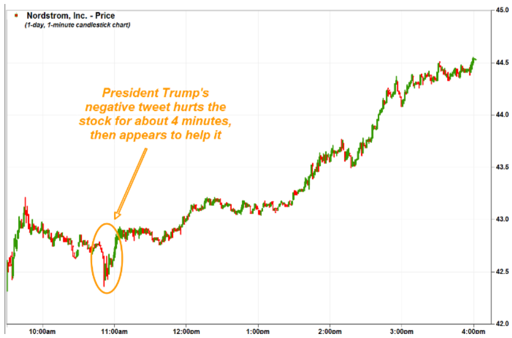


Figure 1. Nordstrom stock prices
Source: marketwatch.com

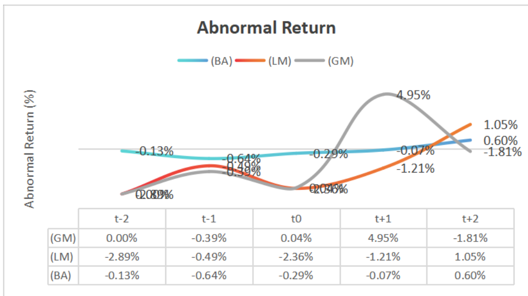
As author mentioned above, some of the studies and literatures results about the impact of Donald Trump's tweet sentiment over stock price are directly proportional (Anwar and Asandimitra 2018; Ge, Kurov, and Wolfe 2019; Guo, Jiao, and Xu 2021), but these narratives may not always hold and the author finds a gap phenomenon. On February 8, 2017, marketwatch.com has reported that President Donald Trump tweeted criticism of Nordstrom's decision to stop selling Ivanka Trump's products, describing the action as unfair and defending his daughter's character. Following the tweet, Nordstrom's stock initially declined by 0.3% to approximately \$42.65 at 10:50 a.m., then quickly dropped further to \$42.32—matching the intraday low recorded shortly after market opening. However, by 10:55 a.m., the stock rebounded above \$42.65, remaining above that level by 11:00 a.m., and by 11:01 a.m., it turned positive for the day and continued to rise (Kilgore 2017).

Another notable finding regarding the gap in the phenomenon of President Donald Trump's tweet sentiment affecting abnormal return, trading volume activity, and volatility is presented in a report by Primack and Vavra published on AXIOS, titled "Trump Tweets Don't Hurt Company Stocks." The article identified six companies that were unaffected by Trump's negative tweet sentiments, suggesting that not all firms experience measurable financial impacts following his online statements (Primack and Vavra 2015).

COMPANY	TWEET TIME	PRE-TWEET PRICE	FEB. 14 OPEN	CHANGE
The New York Times	Nov. 13 6:16 a.m.	$12.25	$16.1	+31.4%
Rexnord	Dec. 2 7:06 p.m.	$20.27	$22.4	+10.5%
Boeing	Dec. 6 5:52 a.m.	$152.16	$167.7	+10.2%
Lockheed	Dec. 12 6:01 p.m.	$253.11	$262.19	+3.6%
General Motors	Jan. 3 4:30 a.m.	$34.84	$36.72	+5.4%
Toyota	Jan. 5 10:14 a.m.	$121.19	$114.34	-5.7%
Nordstrom	Feb. 8 7:51 a.m.	$42.78	$44.31	+3.6%

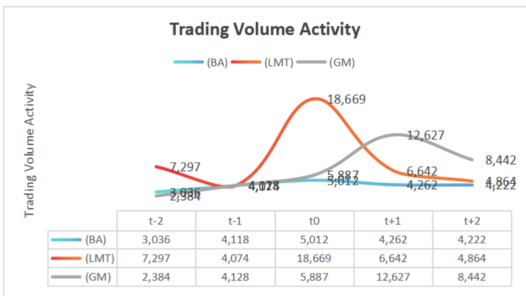
Figure 2. Gap phenomenon sentiment tweet
Source: AXIOS

To validate the credibility of the information from the aforementioned source and to align it with the current research variables, the author calculated abnormal return, trading volume activity, and volatility for three out of the six companies depicted in the referenced image. These companies—Boeing (BA), Lockheed Martin (LMT), and General Motors (GM)—are all listed on the U.S. stock exchange under the S&P 500 index. The calculations utilized formulas outlined in Chapter Three, and the event window was set to five days: two days before the tweet, the day of the tweet, and two days after.



	t-2	t-1	t0	t+1	t+2
(GM)	0.00%	-0.39%	0.04%	4.95%	-1.81%
(LM)	-2.89%	-0.49%	-2.36%	-1.21%	1.05%
(BA)	-0.13%	-0.64%	-0.29%	-0.07%	0.60%

Figure 3. Abnormal return around event window
Source: Output processed from original data using Excel



	t-2	t-1	t0	t+1	t+2
(BA)	3,036	4,118	5,012	4,262	4,222
(LMT)	7,297	4,074	18,669	6,642	4,864
(GM)	2,384	4,128	5,887	12,627	8,442

Figure 4. Trading Volume Activity around event window
Source: Output processed from original data using Excel

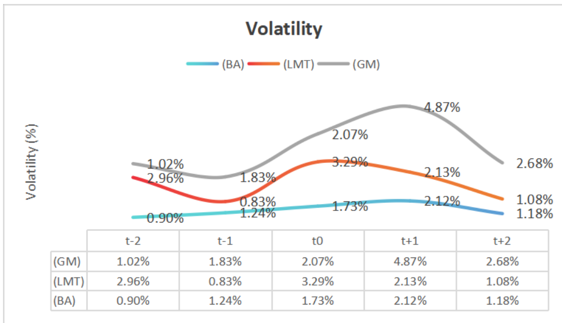


Figure 5. Volatility around event window

Source: Output processed from original data using Excel

Three negatively toned tweets by Donald Trump targeted Boeing (Dec 6, 2016), Lockheed Martin (Dec 12, 2016), and General Motors (Jan 3, 2017), each criticizing excessive costs or outsourcing practices. Market responses varied: abnormal returns increased post-tweet for all three companies, while trading volume activity mostly declined except for GM, and volatility generally rose following the tweets—most significantly for GM, where abnormal return surged from 0.04% to 4.95%, and volatility from 2.07% to 4.87%.

Building on prior studies, this research underscores that tweets by President Donald Trump—regardless of sentiment—have influenced the stock prices of companies he directly mentioned. However, the observed gap phenomenon introduces a contrasting perspective. To further investigate this, the study poses a key question: whether there are significant differences in abnormal return, trading volume, and volatility before and after Trump's tweets about S&P 500-listed companies, based on the sentiment conveyed. By examining these dynamics, the study provides valuable insights not only into financial market behavior but also into the socio-political influence of prominent figures. The findings highlight that such individuals can meaningfully affect both specific stock prices and broader market indices, offering practical implications for investors, financial managers, and arbitrageurs who may leverage algorithmic tools to inform trading decisions.

This study employs five variables—two independent and three dependents—to examine the market impact of President Donald Trump's tweets. The independent variables are: (1) tweet sentiment (X1), represented as a dummy variable with 0 for negative and 1 for positive sentiment, and (2) time (X2), also a dummy variable indicating the event day (0) and the following day (1). These two variables are analyzed for their simultaneous effects on three dependent variables: abnormal return (Y1), trading volume activity (Y2), and volatility (Y3). The event study method is applied to assess market reactions, using estimation and event windows to calculate expected returns (Brans and Scholtens 2020; MacKinlay 1997), while panel data regression is used to determine whether Trump's tweets significantly affect stock performance before and after posting. The research aims to observe and investigate whether such tweets cause measurable changes in the three market indicators, thereby offering valuable insights for investors in making informed decisions based on political figures' market-moving sentiments.

2. Theoretical Background

Efficient Market Hypothesis (EMH): The Efficient Market Hypothesis (EMH), introduced by (Fama 2017) in The Journal of Finance, posits that asset prices fully and accurately reflect all available information at any point in time, making it difficult to consistently achieve returns above the market average on a risk-adjusted basis. The theory classifies market efficiency into three forms: the weak form, where prices reflect only historical price and volume data and align with (Bachelier 1900) Random Walk Theory; the semi-strong form, which incorporates all publicly available information including financial reports and news; and the strong form, which also includes private insider information. Both semi-strong and strong forms are grounded in (Muth 1961) rational expectations theory, suggesting markets rapidly incorporate new data. Empirical support for the semi-strong form is provided by (Benton and Philips 2020), who found that Donald Trump's tweets regarding U.S.–Mexico regulations significantly influenced the volatility of the USD–MXN exchange rate, especially after the tweets were posted, illustrating how political figures with regulatory authority can impact market behavior.

Social Media Twitter: Social media's evolution into a ubiquitous digital interface has redefined how individuals interact and process information, contributing significantly to public sentiment and financial decision-making (Power and Phillips-Wren 2011; Zhong 2021). Twitter, in particular, exhibits measurable influence in shaping market behavior, with studies linking its sentiment to stock movements (Valle-Cruz et al. 2022). The SEC's 2013 endorsement of Twitter as a formal disclosure tool further solidified its credibility within financial ecosystems (Brans and Scholtens 2020). Political figures such as Donald Trump have harnessed its immediacy, yielding varying market outcomes—some studies reported abnormal returns triggered by campaign tweets (Born, Myers, and Clark 2024) while others found negligible effects (Juma'h and Alnsour 2018). These divergent findings underscore the context-dependent nature of social media's impact on capital markets.

Investment, and Capital Market: Investment has become increasingly popular across generations—especially among younger demographics—as a means to build wealth, where its core principles emphasize capital preservation and adequate return, notably through long-term and diversified approaches (Graham and McGowan 2003; Malkiel 1997). Simultaneously, the capital market serves as a vital financial infrastructure enabling companies to raise funds via instruments like stocks and bonds, while offering investors avenues for returns through dividends or capital gains (Chisholm 2003; Rahmah 2019; Rechtschaffen 2009). Defined as a structured system for securities transactions(Abdurrachman 1982) and legally framed by (Undang-Undang Republik Indonesia No. 8 Tahun 1995), it plays a dual role by facilitating business expansion and channeling surplus capital into diverse financial products, such as mutual funds and derivatives (Arifardhani 2020).

Standard and Poor's 500: The S&P 500 serves as a benchmark index representing the U.S. stock market through 500 leading domestic firms meeting stringent criteria for size, liquidity, and financial viability (Dieterle 2017). Highlighting the growing relevance of digital communication, (Kim and Youm 2017) reveal that corporate engagement via Twitter can shape analyst recommendations—particularly when firm-generated content aligns with growth narratives, while negative customer feedback gains influence under institutional amplification. These findings underscore social media's evolving role in financial assessments, where both corporate messaging and public sentiment can inform investment discourse.

Tweet Sentiment Analysis: Sentiment analysis—defined by (Liu 2020) as the study of opinions, emotions, and behaviors toward entities—is rooted in Natural Language Processing (NLP) and intersects with areas such as data mining, now expanding into multimodal domains. The term itself emerged from works by (Dave, Lawrence, and Pennock 2003; Nasukawa and Yi 2003). In political applications, sentiment scores have been linked to electoral trends (Bermingham and Smeaton 2011; O'Connor, Krieger, and Ahn 2010), though concerns remain about accuracy in platforms like Twitter (Chung and Mustafaraj 2011). In finance, sentiment analysis has proven predictive of market indices, with studies indicating that heightened emotional states often precede downturns, while subdued public mood can signal market recovery (Das and Chen 2007).

Hypothesis and Conceptual Framework:

Influence of sentiment tweet, and event-post day on abnormal return.

In the book *Mengenal Saham by* (Wardhani 2022) defines abnormal return as the difference between actual return and expected return, calculated daily to assess stock price movements over specific timeframes. Similarly, (Hartono 2009) emphasizes that abnormal return represents the gap between actual and expected returns. (Brans and Scholtens 2020), in their study "Under His Thumb: The Effect of President Donald Trump's Twitter Messages on The US Stock Market", found that Donald Trump's negatively toned tweets significantly affected the abnormal returns of companies he mentioned, though positively toned tweets showed no significant effect, and the impact was only short-term (intraday). Supporting this, (Ajjoub, Walker, and Zhao 2021) observed that for media companies, positive tweet sentiments had a significant effect on abnormal return, while negative ones did not; conversely, for non-media firms, negative tweets were impactful while positive ones were not. However, (Dumrongvachiraphan and Tangjitprom 2020) challenged the notion of purely short-term effects, finding that negative tweet sentiments led to significant declines in both abnormal return (AR) and trading volume activity (TVA) up to two days post-publication.

Based on the research gap identified through the observations above, the author formulates the first and second hypotheses as follows:

H1: *There is a significant influence in abnormal return of S&P 500-mentioned and listed stocks on President Donald Trump's positive or negative sentiment-related tweets.*

H2: *There is a significant influence in abnormal return of S&P 500-mentioned and listed stocks on event day and one day after President Donald Trump's sentiment-related tweets.*

Influence of sentiment tweet, and event-post day on trading volume activity.

Trading volume reflects the level of market activity and is measured by the number of shares exchanged within a specific period relative to the total available for trading (Ge, Kurov, and Wolfe 2019; Husnan 2005), in their study "Do Investors Care About Presidential Company-Specific Tweets?", found that Donald Trump's tweet sentiments significantly impacted stock prices, volatility, investor attention, and trading volume, particularly when tweets mentioned specific public companies. They noted that these effects were more pronounced before his inauguration and often reversed in subsequent days, emphasizing the role of timing. In contrast, (Gjerstad et al. 2021) concluded that while Trump's tweets strongly influenced stock prices and market uncertainty, they had limited impact on trading volume when the tweet sentiment was positive. Similarly, (Kleczka 2020) found that Trump's company-specific tweets affected trading volume only briefly, with effects dissipating within hours. These insights suggest that while trading volume reactions to political tweets may be short-lived, they hold potential for application in automated trading systems driven by social media sentiment.

Based on the research gap identified through the observations above, the author formulates the second and third hypotheses as follows:

H3: *There is a significant influence in trading volume activity of S&P 500-mentioned and listed stocks on President Donald Trump's positive or negative sentiment-related tweets.*

H4*: There is a significant influence in trading volume activity of S&P 500-mentioned and listed stocks on event day and one day after President Donald Trump's sentiment-related tweets.*

Influence of sentiment tweet, pre-post event, and their interaction on volatility.

In "Stock Market Volatility" by (Gregoriou 2009) defines stock market volatility as the degree of variation in stock prices over time, reflecting uncertainty or risk in the market. He emphasizes that volatility is dynamic and influenced by factors such as market sentiment, economic conditions, and investor behavior. (Guo, Jiao, and Xu 2021), in their study "Trump's Effect on the Chinese Stock Market", found that Donald Trump's tweet sentiments had significant impacts on financial markets, particularly stock prices, trading volume, and volatility, with trade war and tariff-related tweets triggering negative reactions in both U.S. and Chinese markets, while gold prices rose. Similarly, (Nishimura and Sun 2025) discovered that Trump's tweets had a persistent and positive influence on stock volatility in non-U.S. markets, including the UK, Germany, France, and the EU—highlighting the global reach of his sentiment. However, (Audrino, Sigrist, and Ballinari 2020), in "The Impact of Sentiment and Attention Measures on Stock Market Volatility", analyzed sentiment and attention data from platforms like StockTwits, news articles, and search engine queries. While these variables improved volatility forecasts, the economic significance was marginal, and their practical impact on volatility was limited and short-lived.

Based on the research gap identified through the observations above, the author formulates the fifth and sixth hypotheses as follows:

H5: *There is a significant influence in volatility of S&P 500-mentioned and listed stocks on President Donald Trump's positive or negative sentiment-related tweets.*

H6: *There is a significant influence in volatility of S&P 500-mentioned and listed stocks on event day and one day after President Donald Trump's sentiment-related tweets.*

Based on the definitions of variables and their interrelationships discussed previously, the researcher conceptualizes the research framework as follows:

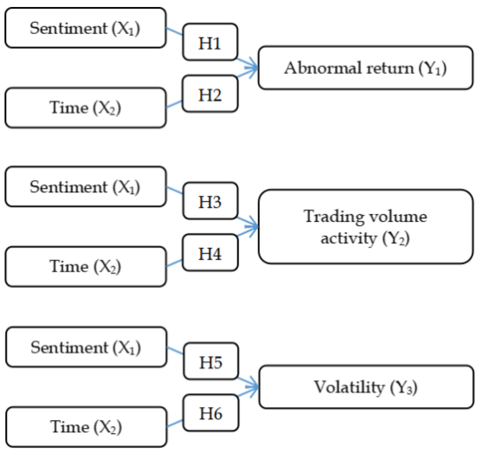


Figure 6. Conceptual framework
Source: Output processed from original data using Canva

3. Methodology

This research adopts a quantitative approach (Balnaves and Caputi 2001) with both descriptive and exploratory purposes, aiming to explain the observed phenomenon and explore relationships or impacts on the dependent variable (Given 2008), particularly issues that require further investigation to find solutions (McNabb 2020). Methodologically, this study applies an event study approach, focusing on differences and impacts before and after a specific event (MacKinlay 1997). The event window follows (Brans and Scholtens 2020) and is divided into two periods: (1) event day (H0), when the tweet was posted before the stock market closed; and (2) post-event (H+1), the day after the tweet, following market opening. This study uses quantitative data with secondary sources (Trinh 2018). The population consists of companies listed on the S&P 500 index (Bajpai 2009), while the sample includes companies meeting these criteria: (1) listed on the S&P 500 between 2016 and 2019; (2) explicitly mentioned by Donald Trump in his tweets; and (3) mentioned within a single tweet thread during the event window, with no other companies mentioned in the same tweet. Using the Python programming language on the Google Collaboratory platform, a program was executed to extract tweets explicitly mentioning companies listed in the S&P 500 index, resulting in the identification of 9,357 relevant tweets. The tweet population was then filtered using a sentiment analysis tool specifically designed for social media data, namely Tweet NLP. This tool has previously been applied in academic research by Hanh Nguyen Phuong (2022), who utilized it to analyze Twitter sentiment for predicting Bitcoin price volatility. The filtering process yielded 326 sentiment-bearing tweets that met the research criteria, comprising 29 units of companies (cross-section) data which were subsequently used as the study sample.

In Research in Education: A Conceptual Introduction, James H. McMillan and Sally Schumacher explain that there are at least four common multi-method strategies for data collection in quantitative research, namely: in-depth interviews, participant observation, completion techniques, and document studies (McMillan and Schumacher 2010). According to (Bungin 2007), document study in quantitative research is a method used to trace historical data, particularly within social research. The types and sources of data used in this study are categorized as follows: (1) the independent variable, X1 (sentiment), is derived from a publicly accessible archive of tweets from @realDonaldTrump prior to account suspension, available at https://www.thetrumparchive.com. Sentiments were classified as positive or negative using Natural Language Processing (NLP) tools, specifically the open-source Tweet NLP program, executed via Python on Google Collaboratory (Hasan, Maliha, and Arifuzzaman 2019; Lavanya et al. 2024; Olusegun et al. 2023; Weerasooriya, Perera, and Liyanage 2016). (2) The first dependent variable, abnormal return, uses data on actual stock prices, returns, and expected returns, sourced from Yahoo Finance, Bloomberg, and Python's `yfinance` library. (3) The second dependent variable, trading volume, includes daily transaction volumes and quarterly share outstanding, also collected from Yahoo Finance, Nasdaq, Bloomberg, and `yfinance`. (4) The third dependent variable, stock volatility, is calculated using daily high-low price data via a simple high-low range formula, with data accessed from the same financial sources. (5) Lastly, the reference stocks for the study are drawn from the S&P 500 Index, with component and sector information retrieved from Yahoo Finance. All data extraction was performed using Python programming within the Google Collaboratory platform.

As previously explained, there are three dependent variables in this study, which are abnormal return, trading volume activity, and volatility. Mathematical calculations were conducted to obtain the data for each variable. To calculate abnormal return, the formula referenced in the study by (Strong 1992) was utilized, which is presented as follows:

$$\boldsymbol{AR_t = R_t - E(R_t)}$$

actual return (Rt) can be calculated using the formula as follows:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Several models can be utilized to calculate expected return; in this study, the author employed the market-adjusted model estimation method, as proposed by (Brown and Warner 1985) and (Schaltegger, Bennett, and Burritt 2006). The formula for calculating expected return (ERt) using the market-adjusted model, which was also applied in the study by (Anwar and Asandimitra 2018), is presented as follows:

$$R_{i,j} = R_{M,j}$$

The formula for calculating trading volume activity is as follows (Anwar and Asandimitra 2018):

$$\mathbf{TVA} = \frac{number\ of\ shares\ i\ traded\ at\ time\ t}{number\ of\ shares\ i\ outstanding\ at\ time\ t}$$

The formula used to calculate volatility is as follows (Alizadeh, Brandt, and Diebold 1999):

$$V_{s,t} = ln(H_t) - ln(L_t)$$

All of those formulas are calculated using python language program to fasten the calculation. The panel regression model used to examine the effect of three dummy variables—tweet sentiment, and event time—on each dependent variable, namely Abnormal Return (AR), Trading Volume Activity (TVA), and Volatility (V), is divided into three formulas that will be determined for the fittest panel regression model by conducting three econometrical statistic tests model (Cameron and Trivedi 2005; Watson and Teelucksingh 2002) which are Chow Test, Hausman Test, and Lagrange Multiplier Test as follows:

Common Effect Model/Pooled OLS (Gujarati 2004; Webel 2011) :

$$Y_{i,t} = \alpha + \beta_1 \times X_{1,i,t} + \beta_2 \times X_{2,i,t} + \varepsilon_{i,t}$$

Fixed Effect Model (Best and Wolf 2013; Webel 2011):

$$Y_{i,t} = \alpha_1 + \beta_1 \times X_{1,i,t} + \beta_2 \times X_{2,i,t} + \varepsilon_{i,t}$$

Random Effect Model (Best and Wolf 2013; Webel 2011):

$$Y_{i,t} = \alpha + \beta_1 \times X_{1,i,t} + \beta_2 \times X_{2,i,t} + u_i + \varepsilon_{i,t}$$

Classical assumption testing is conducted to evaluate whether the applied regression model is appropriate for the research context (Juliandi, Irfan, and Manurung 2023).

Prior to conducting regression analysis and hypothesis testing, a series of classical assumption tests must be performed to ensure the model is free from assumption violations and satisfies the conditions required for producing a valid linear relationship (Waty et al. 2023). The types of classical assumption tests commonly employed in panel data regression include: (1) normalcy test (Shapiro and Wilk 1965); (2) multicollinearity test (Gujarati 2004; Hines, Montgomery, and Borror 2008); and (3) heteroskedasticity test (Gujarati 2004; Santoso 2000). Hypothesis testing is used to assess the influence of independent variables on dependent variables at a 5% significance level. This study uses two tests: the t-test (Semenick 1990) and the F-test (Tiku 1967), and coefficient determination R^2 (Ozer 1985).

4. Empirical Findings/Result

Descriptive Statistic

According to (Bajpai 2009) in his book "Business Statistics", descriptive statistics is the process of summarizing and interpreting data to derive meaningful insights. When data is collected through surveys or studies, it often appears disorganized and difficult to comprehend. Descriptive statistics offers a set of tools—such as measures of central tendency like mean, median, and mode—as well as measures of dispersion including range, quartiles, and standard deviation, which help clarify data patterns and variability. These methods enable researchers to recognize underlying trends, thereby facilitating more accurate conclusions.

Table 1. Descriptive Statistic

Variables	Obs	Mean	Std. Dev.	Min	Max
sentiment	326	.334	.472	0	1
time	326	.5	.501	0	1
AR	326	-1172.485	17742.189	-198627	44583
TVA	326	2550000	4160000	321	37670987
V	326	21613.233	14349.829	1183	147667

Source: Output processed from original data usingm STATA

The table above presents the statistical description of the research variables. The variables sentiment and time are ordinal in nature and are treated as dummy variables. Abnormal return is measured in percentage units based on stock price differences, trading volume activity is expressed in the number of shares traded, and volatility is measured using logarithmic units. The dataset comprises 326 observations.

Panel Regression Model Specification Test

Table 2. Result of Specification Test for Abnormal Return

AR	Prob > F	Prob > chibar2
Uji Chow	0.9966	
Uji Langragian-Multiplier		1.0000

Source: Output processed from original data using STATA

Since the values of Prob > F and Prob > chibar² exceed 0.05—specifically 0.9966 and 1.0000 respectively—the appropriate panel data regression model for the dependent variable abnormal return is the Common Effect Model (CEM).

Table 3. Result of Specification Test for Trading Volume Activity

TVA	Prob > F	Prob > chi2
Uji Chow	0.0000	
Uji Hausman		0.9904

Source: Output processed from original data using STATA

Then, the value of Prob > F in the Chow test is less than 0.05 (0.0000), indicating the rejection of the Common Effect Model, and the value of Prob > chibar² is greater than 0.05 (0.9904), suggesting no significant difference between the Fixed and Random Effect models, the appropriate panel data regression model for the dependent variable trading volume activity is the Random Effect Model (REM).

Table 4. Result of Specification Test for Volatility

V	Prob > F	Prob > chi2
Uji Chow	0.0000	
Uji Hausman		0.4435

Source: Output processed from original data using STATA

And, the value of Prob > F in the Chow test is less than 0.05 (0.0000), indicating that the Common Effect Model should be rejected, and the value of Prob > chibar² is greater than 0.05 (0.4435), suggesting that there is no significant difference between the Fixed and Random Effect models, the appropriate panel data regression model for the dependent variable volatility is the Random Effect Model (REM).

Classical Assumption Test

Normalcy Test

Normality testing aims to determine whether the dependent and independent variables in a panel data regression model follow a normal distribution. A regression model is considered to meet the normality assumption when the data points align along the diagonal line, indicating distribution conformity (Juliandi, Irfan, and Manurung 2023). According to (Waty et al. 2023), a well-specified regression model should exhibit normal distribution characteristics. In this study, the normality test is conducted using the (Shapiro and Wilk 1965), which suggests data are normally distributed when the significance value exceeds 5% (0.05), based on a 5% significance level.

Table 5. Result of Normalcy Test

Variable	Obs	W	V	z	Prob>z
AR	326	0.717	65.019	9.838	0.000
TVA	326	0.649	80.477	10.341	0.000
V	326	0.805	44.653	8.953	0.000

Source: Output processed from original data using STATA

The table indicates that none of the variables used in the model exhibit a normal distribution, as all significance values fall below the 5% threshold (Prob>z < 0.05). This outcome is typical, considering panel data's inherent limitations in achieving normality and the asymptotic nature of its estimators (Baltagi 2021; Levin, Lin, and James Chu 2002). Nevertheless, the Central Limit Theorem (CLT) posits that the sampling distribution of the mean tends toward normality given a sufficiently large number of observations, regardless of the underlying data distribution. Hence, the normality assumption is not an essential prerequisite for panel data models characterized by asymptotic properties (Gujarati 2004).

Multicollinearity Test

Multicollinearity refers to a phenomenon in regression samples where independent variables—though not linearly related within the population—may appear correlated in specific analyzed samples (Gujarati 2004). Its presence is commonly assessed through the Variance Inflation Factor (VIF), which should remain below thresholds of 4 or 5 to indicate acceptable levels of multicollinearity (Hines, Montgomery, and Borror 2008).

Table 6. Result of Multicollinearity Test

Variabel	VIF	1/VIF
Sentiment	1.000	0.999958
Time	1.000	0.999958
Mean VIF	1.000	

Source: Output processed from original data using STATA

It can be concluded that the dummy independent variables utilized in the analysis—namely sentiment and time—do not exhibit signs of multicollinearity, as evidenced by their respective Variance Inflation Factor (VIF) values being below 10. Consequently, the independent variables in the panel data regression can be considered statistically independent from one another and are suitable for inclusion in the regression model.

Heteroscedasticity Test

Heteroskedasticity, derived from “hetero” (difference) and “scedasticity” (dispersion), refers to a condition in regression models where the variance of residuals varies across observations, in contrast to homoskedasticity, which implies constant variance (Gujarati 2004). It is diagnosed by examining residual patterns: if plotted points form a discernible pattern, heteroskedasticity is present; if the points are randomly scattered around zero on the Y-axis without a clear structure, heteroskedasticity is absent. A sound regression model should ideally exhibit homoskedasticity (Santoso 2000).

Table 7. Result of Heteroskedasticity Test for Abnormal Return

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity Assumption: Normal error terms Variable: Fitted values of AR	chi2(1)	Prob > chi2
H0: Constant variance	38.68	0.0000

Source: Output processed from original data using STATA

The presence of heteroskedasticity in the abnormal return model, indicated by prob > chi2 = 0.0000, below 0.05 threshold, was addressed using Feasible General Least Square (GLS) regression for complex panel data (Hoechle 2007). For models with trading volume activity and volatility, the Random Effect Model was used, allowing classical tests to be bypassed, though robust regression was applied to control for potential autocorrelation (Agus and Imamudin 2014; Hoechle 2007; Napitupulu et al. 2021).

Panel Regression Analysis

Table 8. Feasible Generalized Least Square Panel Regression for AR

AR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sentiment	-280.662	673.712	-0.42	.677	-1601.114	1039.789	
time	2197.101	655.546	3.35	.001	912.253	3481.948	***
Constant	-873.522	622.62	-1.40	.161	-2093.835	346.79	

Mean dependent var	-1172.485	SD dependent var	17742.189
Number of obs	326	Chi-square	11.413
		Prob > chi2	0.0033

*** *p<.01*, ** *p<.05*, * *p<.1*

Source: Output processed from original data using STATA

The panel regression results using the Feasible Generalized Least Squares (FGLS) method reveal a significant positive effect of the time variable (day H+1) on abnormal return, with a coefficient of 2197.101 and *p*-value of 0.001, indicating a positive market reaction following the tweet. In contrast, the sentiment variable shows a negative but statistically insignificant effect (coefficient = -280.662; *p*-value = 0.677), suggesting no influence on abnormal return. The constant value of -873.522 represents the average abnormal return on day H under negative sentiment. Overall, the model is statistically significant as indicated by the Chi-square test ($\chi^2 = 11.413$; $p = 0.0033$), confirming joint contributions of the included variables to abnormal return variation.

Table 9. Result of Random Effect Model with Robust Std. Err. Regression for TVA

TVA	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sentiment	324620.04	721243.23	0.45	.653	-1088990.7	1738230.8	
time	299226.92	164600.95	1.82	.069	-23385.008	621838.86	*
Constant	2335062.9	562486.07	4.15	0	1232610.5	3437515.4	***

Mean dependent var	2549255.009	SD dependent var	4162144.309
Overall r-squared	0.003	Number of obs	326
Chi-square	3.606	Prob > chi2	0.165
R-squared within	0.006	R-squared between	0.000

*** *p<.01*, ** *p<.05*, * *p<.1*

Source: Output processed from original data using STATA

The panel regression results using a Random Effect Model with robust standard errors reveal a positive and marginally significant effect of the time variable (H+1) on trading volume activity (TVA), with a coefficient of 299.226 and a *p*-value of 0.069, suggesting increased trading volume post-event. In contrast, sentiment shows no significant effect (p = 0.653). The constant value of 2,335,062 represents the average TVA on day H under negative sentiment. However, the overall model is not statistically significant (Chi-square = 3.606; p = 0.165).

Table 10. Result of Random Effect Model with Robust Std. Err. Regression for V

V	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
sentiment	-.003	.001	-2.83	.005	-.005	-.001	***
time	.001	.001	0.80	.425	-.001	.003	
Constant	.022	.002	12.19	0	.018	.025	***

Mean dependent var	0.023	SD dependent var	0.014
Overall r-squared	0.011	Number of obs	326
Chi-square	8.624	Prob > chi2	0.013
R-squared within	0.004	R-squared between	0.122

*** *p<.01,* ** *p<.05,* * *p<.1*

Source: Output processed from original data using STATA

The random effect regression with robust standard errors reveals a significant negative impact of sentiment on volatility (V), with a coefficient of -0.003 and p-value of 0.005, indicating that positive sentiment contributes to lowering stock price volatility. Conversely, the time variable shows no significant effect (p = 0.425). The constant value of 0.022 reflects average volatility on day H under negative sentiment. Overall, the model is statistically significant, supported by a Chi-square test result of χ^2 = 8.624 (p = 0.013).

t-Test

The T-test is a statistical method used to compare the means of two groups and determine if an observed difference or relationship is significant (Semenick 1990). Partial hypothesis tests (t-tests) from panel regression models indicate that the time variable significantly increases abnormal returns (AR) post-event (p = 0.001), leading to the rejection of $H2_0$ and confirming a positive market reaction the day after President Donald Trump's tweet. However, sentiment does not significantly affect AR (p > 0.05), nor does the constant differ meaningfully from zero, resulting in non-rejection of $H1_0$. Regarding trading volume activity (TVA), time exerts a marginally significant positive influence (p = 0.069), supporting $H4_0$, while sentiment remains statistically insignificant (p = 0.653), sustaining $H3_0$. For volatility (V), sentiment displays a significant negative effect (p = 0.005), indicating that positive sentiment reduces stock price fluctuations, thus $H5_0$ is rejected, whereas time again shows no significant impact (p = 0.425), leaving $H6_0$ unrefuted.

F-Test

The F-test determines whether independent variables jointly have a significant effect on the dependent variable. If the p-value is below 0.05, the null hypothesis (H_0) is rejected, indicating simultaneous influence (Tiku 1967). Building on the simultaneous hypothesis tests (F-tests), the Chi-square statistic from the FGLS model ($\chi^2 = 11.413$; $p = 0.0033$) confirms that the sentiment and time variables jointly have a significant impact on abnormal return (AR), suggesting that tweets by President Trump can meaningfully influence market reactions the day after publication—even if not every variable shows significance individually. This underscores the market's responsiveness to both timing and tone of public communication. In contrast, the Random Effect Model yields a Chi-square value of 3.606 ($p = 0.165$) for trading volume activity (TVA), indicating that sentiment and time together do not significantly drive volume changes, despite partial indications. Meanwhile, the joint significance test for volatility returns a p-value of 0.013, signifying that sentiment and timing factors collectively shape fluctuations in stock prices, especially among companies explicitly mentioned in the tweets. These findings highlight the broader market relevance of influential public statements, not just in returns but also in volatility dynamics.

Coefficient of Determination (R Square)

R-squared (R^2) measures how well a regression model explains data variation—higher values mean better fit, while values near 0 show weak explanatory power (Ozer 1985) Because the Feasible General Least Squares (GLS) panel regression model for the abnormal return (AR) variable does not display the R-squared value, the coefficient of determination must be calculated manually using the following formula: (Khorrami et al. 2025):

$$\boldsymbol{R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{1.017 \times 10^{11}}{1.024 \times 10^{11}} = 1 - 0.9931 \approx 0.0069}$$

The R^2 value of 0.0069 indicates that tweet sentiment and timing explain just 0.69% of abnormal return variation, while the remaining 99.31% is influenced by other unobserved factors. R-squared values of 0.003 for trading volume activity (TVA) and 0.011 for volatility (V) indicate minimal explanatory power—just 0.3% and 1.1%, respectively. For TVA, within-company variation is barely explained ($R^2 = 0.006$), and between-firm variation is nearly absent ($R^2 = 0.000$). In contrast, the volatility model explains 0.4% of variation within firms and a more notable 12.2% across firms (R^2 between = 0.122).

Low R^2 values in event-based financial studies are common and not necessarily a flaw; they reflect the complex and unpredictable nature of stock markets, which are influenced by various external factors such as macroeconomic news, investor expectations, and noise trading. In this context, a low R^2 signals the inherent difficulty of capturing stock price variability using simplified models (Chang and Luo 2010; Polat and Sevil 2014).

5. Discussion

Hypothesis testing reveals that sentiment in President Donald Trump's tweets does not significantly affect abnormal returns of mentioned stocks, suggesting the market does not meaningfully differentiate between positive and negative tones. Within the semi-strong form of the Efficient Market Hypothesis (EMH), this supports the view that public information is efficiently reflected in prices unless it introduces novel insights (Ajjoub, Walker, and Zhao 2021; Brans and Scholtens 2020). Conversely, the time variable shows a significant positive effect, indicating a delayed market reaction, which challenges EMH by implying that investors may require time to fully interpret tweet content. This finding aligns with previous studies (Anwar and Asandimitra 2018; Born, Myers, and Clark 2024; Dumrongvachiraphan and Tangjitprom 2020; Guo, Jiao, and Xu 2021; Ranco et al. 2015).

Hypothesis testing on the sentiment variable toward trading volume activity (TVA) indicates no significant impact of tweet sentiment—positive or negative—on the TVA of companies directly mentioned by President Donald Trump. This suggests the market did not exhibit substantial changes in trading behavior based solely on tweet tone. Within the framework of the semi-strong form of the Efficient Market Hypothesis (EMH), this aligns with the notion that public information, including statements from public figures, is efficiently absorbed by investors unless accompanied by materially new data (Gjerstad et al. 2021). Conversely, the time variable, representing post-event day, shows a positive and marginally significant influence on TVA, implying a delayed market response to tweet content. This delay suggests the market may require additional time to interpret potentially complex or politically nuanced messages, challenging the immediate reaction assumption of the semi-strong EMH (Ge, Kurov, and Wolfe 2019; Kleczka 2020).

Hypothesis testing reveals that sentiment in President Donald Trump's tweets has a significant negative effect on stock volatility, indicating that positive sentiment contributes to market stabilization by reducing uncertainty and price fluctuations. This supports the semi-strong form of the Efficient Market Hypothesis (EMH), suggesting that markets efficiently incorporate not just the presence but also the emotional tone of public information into risk expectations (de Area Leão Pereira et al. 2018; Audrino, Sigrist, and Ballinari 2020; Benton and Philips 2020; Ge, Kurov, and Wolfe 2019; Guo, Jiao, and Xu 2021; Nishimura and Sun 2025). In contrast, the time variable—distinguishing between event day and post-event day—shows no significant effect on volatility, indicating immediate market absorption of information without sustained price disruptions, consistent with prior findings (Sul, Dennis, and Yuan 2017).

6. Conclusions

This study concludes that tweets by President Donald Trump do not consistently trigger immediate changes in stock market performance for directly mentioned companies. While tweet sentiment does not significantly affect abnormal return or trading volume, it has a significant negative impact on volatility, suggesting a stabilizing effect. Meanwhile, the post-event timing variable significantly influences abnormal return and shows marginal significance in trading activity. These findings highlight that the market may not operate in full alignment with the semi-strong form of the Efficient Market Hypothesis (EMH), as investor responses to public information appear delayed and selective.

Future research is advised to incorporate more refined sentiment analysis techniques, such as polarity scales or machine learning-based methods, along with additional control variables like market conditions or macroeconomic factors. These enhancements would yield more comprehensive and precise insights into market reactions to public information shared via social media.

References:

Abdurrachman, A. (1982). *Ensiklopedia ekonomi, keuangan dan perdagangan (Inggris-Indonesia)*. Pradnya Paramita. https://books.google.co.id/books?id=GTgkAAAAMAAJ

Abramson, A. (2017, April 12). President Trump says the U.S. dollar is 'too strong'. *Time Magazine*. http://time.com/money/4737106/donald-trump-usdollar-too-strong/

Agus, T. B., & Imamudin, Y. (2014). *Elektronik data prosesing (SPSS 15 dan EVIEWS 7)*. Danisa Media.

Ajjoub, C., Walker, T., & Zhao, Y. (2021). Social media posts and stock returns: The Trump factor. *International Journal of Managerial Finance, 17*(2), 185–213. https://doi.org/10.1108/IJMF-02-2020-0068

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (1999). Range-based estimation of stochastic volatility models or exchange rate dynamics are more interesting than you think. *Wharton FIC Working Paper, 1*(1), 00–32. https://doi.org/10.2139/ssrn.231165

Anwar, F., & Asandimitra, N. (2018). Analisis perbandingan abnormal return, trading volume activity, dan bid-ask spread sebelum dan sesudah stock split. *BISMA (Bisnis dan Manajemen), 7*(1), 34–44. https://doi.org/10.26740/bisma.v7n1.p34-44

de Area Leão Pereira, E. J., da Silva, M. F., da Cunha Lima, I. C., & Pereira, H. B. B. (2018). Trump's effect on stock markets: A multiscale approach. *Physica A: Statistical Mechanics and its Applications, 512*, 241–247. https://doi.org/10.1016/j.physa.2018.08.069

Arifardhani, Y. (2020). *Hukum pasar modal di Indonesia: Dalam perkembangan*. Prenada Media. https://books.google.co.id/books?id=uEsHEAAAQBAJ

Audrino, F., Sigrist, F., & Ballinari, D. (2020). The impact of sentiment and attention measures on stock market volatility. *International Journal of Forecasting, 36*(2), 334–357. https://doi.org/10.1016/j.ijforecast.2019.05.010

Bachelier, L. (1900). Théorie de la spéculation. *Annales scientifiques de l'École Normale Supérieure, 17*(3), 21–86. Gauthier-Villars.

Bajpai, N. (2009). *Business statistics*. Pearson. https://books.google.co.id/books?id=LIhtLLsyO6AC

Balnaves, M., & Caputi, P. (2001). *Introduction to quantitative research methods: An investigative approach*. SAGE Publications. https://books.google.co.id/books?id=Jz-0aaJAR_0C

Baltagi, B. H. (2021). *Econometric analysis of panel data*. Springer International Publishing. https://books.google.co.id/books?id=h6QjEAAAQBAJ

Benton, A. L., & Philips, A. Q. (2020). Does the @realDonaldTrump really matter to financial markets? *American Journal of Political Science, 64*(1), 169–190. https://doi.org/10.1111/ajps.12465

Bermingham, A., & Smeaton, A. F. (2011). On using Twitter to monitor political sentiment and predict election results. *Centre for Sensor Web Technologies School of Computing, 1*(1). https://doras.dcu.ie/16670/

Best, H., & Wolf, C. (2013). *The SAGE handbook of regression analysis and causal inference*. SAGE Publications. https://books.google.co.id/books?id=Q9rSAwAAQBAJ

Born, J. A., Myers, D. H., & Clark, W. (2024). *Trump tweets and the efficient market hypothesis*. Boston. https://doi.org/10.2139/ssrn.2973186

Brans, H., & Scholtens, B. (2020). Under his thumb: The effect of President Donald Trump's Twitter messages on the US stock market. *PLOS ONE, 15*(3), e0229931. https://doi.org/10.1371/journal.pone.0229931

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics, 14*(1), 3–31. https://doi.org/10.1016/0304-405X(85)90042-X

Bungin, B. (2007). *Penelitian kualitatif: Komunikasi, ekonomi, kebijakan publik, dan ilmu sosial lainnya*. Kencana.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications* (1st ed.). Cambridge University Press. https://books.google.co.id/books?id=Zf0gCwxC9ocC

Chang, E. C., & Luo, Y. (2010). R-squared, noise, and stock returns. *SSRN*. https://doi.org/10.2139/ssrn.1572508

Chisholm, A. M. (2003). *An introduction to capital markets: Products, strategies, participants*. Wiley. https://books.google.co.id/books?id=2FEJdcRrP7sC

Chung, J., & Mustafaraj, E. (2011). Can collective sentiment expressed on Twitter predict political elections? In *Proceedings of the AAAI Conference on Artificial Intelligence* (pp. 1770–1771).

Connell, D. J. (2015). *Institutional investing: How social media informs and shapes the investing process*. https://www.greenwich.com/asset-management/institutional-investing-how-social-media-informs-and-shapes-investing-process

Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science, 53*(9), 1375–1388. https://doi.org/10.1287/mnsc.1070.0704

Dave, K., Lawrence, S., & Pennock, D. M. (2003). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *Proceedings of the 12th International Conference on World Wide Web (WWW '03)*(pp. 519–528). Association for Computing Machinery. https://doi.org/10.1145/775152.775226

Deagon, B. (2018, April 2). Trump hits Amazon again on taxes, using post office as 'delivery boy'. *Investor.com*. https://www.investors.com/news/technology/trump-tweets-hurt-amazon-stock/

Dieterle, D. A. (2017). *Economics: The definitive encyclopedia from theory to practice* (Vols. 1–4). Bloomsbury Publishing. https://books.google.co.id/books?id=jOTNEAAAQBAJ

Dumrongvachiraphan, W., & Tangjitprom, N. (2020). Trump's Twitter effect on financial indexes. In *AU Hybrid International Conference 2024 on Entrepreneurship & Sustainability in the Digital Era* (pp. 319–332). Assumption University of Thailand. https://assumptionjournal.au.edu/index.php/icesde/article/view/4968

Fama, E. F. (2017). Efficient capital markets: A review of theory and empirical work. In J. H. Cochrane & T. J. Moskowitz (Eds.), *Selected papers of Eugene F. Fama* (pp. 76–121). University of Chicago Press. https://doi.org/10.7208/9780226426983-007

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance, 64*(5), 2023–2052. https://doi.org/10.1111/j.1540-6261.2009.01493.x

Ge, Q., Kurov, A., & Wolfe, M. H. (2019). Do investors care about presidential company-specific tweets? *Journal of Financial Research, 42*(2), 213–242. https://doi.org/10.1111/jfir.12177

Given, L. M. (2008). *The SAGE encyclopedia of qualitative research methods* (Vols. 1–2). SAGE Publications. https://books.google.co.id/books?id=IFrb6IPLISEC

Gjerstad, P., Meyn, P. F., Molnár, P., & Næss, T. D. (2021). Do President Trump's tweets affect financial markets? *Decision Support Systems, 147*, 113577. https://doi.org/10.1016/j.dss.2021.113577

Graham, B., & McGowan, B. (2003). *The intelligent investor*. HarperBusiness Essentials.

Gregoriou, G. N. (2009). *Stock market volatility*. Taylor & Francis. https://books.google.co.id/books?id=E2dEAQAACAAJ

Gujarati, D. (2004). *Basic econometrics* (4th ed., L. Sutton, Ed.). McGraw-Hill/Irwin. https://www.academia.edu/40263427/BASIC_ECONOMETRICS_FOURTH_EDITION

Guo, S., Jiao, Y., & Xu, Z. (2021). Trump's effect on the Chinese stock market. *Journal of Asian Economics, 72*, 101267. https://doi.org/10.1016/j.asieco.2021.101267

Hartono, J. (2009). *Teori portofolio dan analisis investasi* (Edisi 6). BPFE Yogyakarta.
Hasan, M. R., Maliha, M., & Arifuzzaman, M. (2019). Sentiment analysis with NLP on Twitter data. In *2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2)* (pp. 1–4). IEEE. https://doi.org/10.1109/IC4ME247184.2019.9036670
Hines, W. W., Montgomery, D. C., Goldman, D. M., & Borror, C. M. (2008). *Probability and statistics in engineering*. John Wiley & Sons.
Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal, 7*(3), 281–312. https://doi.org/10.1177/1536867X0700700301
Husnan, S. (2005). *Dasar-dasar teori portofolio dan analisis sekuritas* (4th ed.). AMP YKPN. https://e-library.nobel.ac.id/index.php?p=show_detail&id=1813
Indonesia. (1995). *Undang-Undang Republik Indonesia Nomor 8 Tahun 1995 tentang pasar modal*. Otoritas Jasa Keuangan. https://www.ojk.go.id/id/kanal/pasar-modal/regulasi/undang-undang/Documents/Pages/undang-undang-nomor-8-tahun-1995-tentang-pasar-modal/UU%20Nomor%208%20Tahun%201995%20(official).pdf
Juliandi, A., Irfan, I., & Manurung, S. (2023). *Metodologi penelitian bisnis: Konsep dan aplikasi* (Revised ed., F. Zulkarnain, Ed.). UMSU Press.
Juma'h, A., & Alnsour, Y. (2018). Using social media analytics: The effect of President Trump's tweets on companies' performance. *Journal of Accounting and Management Information Systems, 17*, 100–121.
Khorrami, M. K., Shahverdi, M. A., Asadian, M., Shirinnejad, M., Mohammadi, M., Shirian, A. Z., & Hajiseyedrazi, Z. S. (2025). Combining ACE, PLS-R, and SVM-R for rapid detection of adulteration in saffron samples by diffuse reflectance infrared Fourier transform spectroscopy. *Food Control, 168*, 110853. https://doi.org/10.1016/j.foodcont.2024.110853
Kilgore, T. (2017, February 8). Nordstrom recovers from Trump's 'Terrible!' tweet in just 4 minutes. *MarketWatch*. https://www.marketwatch.com/story/nordstrom-recovers-from-trumps-terrible-tweet-in-just-4-minutes-2017-02-08
Kim, E. H., & Youm, Y. N. (2017). How do social media affect analyst stock recommendations? Evidence from S&P 500 electric power companies' Twitter accounts. *Strategic Management Journal, 38*(13), 2599–2622. https://doi.org/10.1002/smj.2678
Kleczka, J. (2020). *The effect of President Trump's company-specific tweets on company's stocks* (Honors thesis). University of Richmond. https://scholarship.richmond.edu/honors-theses/1484
Lavanya, B. N., Rathnam, A., Appaji, A., Kiran, K., Shenoy, P. D., & Venugopal, K. R. (2024). LLM GPT-3.5 study for sentiment analysis across Utkarsh server, Ohio supercomputer, Google Colab and PC. *Results in Engineering, 24*, 103218. https://doi.org/10.1016/j.rineng.2024.103218

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics, 108*(1), 1–24. https://doi.org/10.1016/S0304-4076(01)00098-7

Liu, B. (2020). *Sentiment analysis: Mining opinions, sentiments, and emotions*. Cambridge University Press. https://books.google.co.id/books?id=PdX7DwAAQBAJ

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13–39.

Malkiel, B. G. (1997). A random walk down Wall Street. *Business Economics, 32*(2), 74–76.

McMillan, J. H., & Schumacher, S. (2010). *Research in education: Evidence-based inquiry*. Pearson.

McNabb, D. E. (2020). *Research methods for political science: Quantitative, qualitative and mixed method approaches.* Taylor & Francis. https://books.google.co.id/books?id=1GQPEAAAQBAJ

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica, 29*(3), 315–335. https://doi.org/10.2307/1909635

Napitupulu, R. B., Simanjuntak, T. P., Hutabarat, L., Damanik, H., Harianja, H., Sirait, R. T. M., & Tobing, C. E. R. L. (2021). *Penelitian bisnis, teknik dan analisa dengan SPSS-STATA-Eviews.*

Nasukawa, T., & Yi, J. (2003). Sentiment analysis: Capturing favorability using natural language processing. In *Proceedings of the 2nd International Conference on Knowledge Capture* (pp. 70–77). Association for Computing Machinery. https://doi.org/10.1145/945645.945658

Nishimura, Y., & Sun, B. (2025). Impacts of Donald Trump's tweets on volatilities in the European stock markets. *Finance Research Letters, 72,* 106491. https://doi.org/10.1016/j.frl.2024.106491

O'Connor, B., Krieger, M., & Ahn, D. (2010). TweetMotif: Exploratory search and topic summarization for Twitter. *Proceedings of the International AAAI Conference on Web and Social Media, 4*(1), 384–385. https://doi.org/10.1609/icwsm.v4i1.14008

Olusegun, R., Oladunni, T., Audu, H., Houkpati, Y. A. O., & Bengesi, S. (2023). Text mining and emotion classification on Monkeypox Twitter dataset: A deep learning-natural language processing (NLP) approach. *IEEE Access, 11,* 49882–49894. https://doi.org/10.1109/ACCESS.2023.3277868

Ozer, D. J. (1985). Correlation and the coefficient of determination. *Psychological Bulletin, 97*(2), 307. https://psycnet.apa.org/buy/1985-19147-001

Polat, A., & Sevil, G. (2014). Relations between market liquidity and new listings: Istanbul Stock Exchange (BIST) evidence. *International Journal of Business and Social Science, 5*(2). https://www.researchgate.net/profile/Alp-Polat/publication/286360122

Power, D. J., & Phillips-Wren, G. (2011). Impact of social media and Web 2.0 on decision-making. *Journal of Decision Systems, 20*(3), 249–261. https://doi.org/10.3166/jds.20.249-261

Primack, D., & Vavra, S. (2015). Trump tweets don't hurt company stocks. *AXIOS,* 0–1. https://www.axios.com/2017/12/15/trump-tweets-dont-hurt-company-stocks-1513300446
Qiu, L., Rui, H., & Whinston, A. (2013). Social network-embedded prediction markets: The effects of information acquisition and communication on predictions. *Decision Support Systems,* *55*(4), 978–987. https://doi.org/10.1016/j.dss.2013.01.007
Rahmah, M. (2019). *Hukum pasar modal.* Prenada Media. https://books.google.co.id/books?id=nDu2DwAAQBAJ
Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. (2015). The effects of Twitter sentiment on stock price returns. *PLOS ONE, 10*(9), e0138441. https://doi.org/10.1371/journal.pone.0138441
Rechtschaffen, A. N. (2009). *Capital markets, derivatives and the law.* Oxford University Press. https://books.google.co.id/books?id=-NznCwAAQBAJ
Revesz, R. (2017). Toyota loses $1.2bn in value five minutes after Donald Trump's tweet. *Independent.*https://www.independent.co.uk/news/world/americas/toyota-1-2bn-value-plummet-shares-stock-market-donald-trump-tweet-move-mexico-tax-a7512096.html
Santoso, S. (2000). *Buku latihan SPSS: Statistik parametrik.* Elex Media Komputindo. https://books.google.co.id/books?id=n6sQcgAACAAJ
Schaltegger, S., Bennett, M., & Burritt, R. (2006). *Sustainability accounting and reporting.* Springer. https://books.google.co.id/books?id=UENo_JRfSRQC
Semenick, D. (1990). Tests and measurements: The t-test. *Strength & Conditioning Journal,* *12*(1), 36–37. https://journals.lww.com/nsca-scj/citation/1990/02000/TESTS_AND_MEASUREMENTS__The_T_test.8.aspx
Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika,* *52*(3–4), 591–611. https://doi.org/10.1093/biomet/52.3-4.591
Strong, N. (1992). Modelling abnormal returns: A review article. *Journal of Business Finance & Accounting, 19*(4), 533–553. https://doi.org/10.1111/j.1468-5957.1992.tb00643.x
Sul, H. K., Dennis, A. R., & Yuan, L. (2017). Trading on Twitter: Using social media sentiment to predict stock returns. *Decision Sciences, 48*(3), 454–488. https://doi.org/10.1111/deci.12229
Tiku, M. L. (1967). Tables of the power of the F-test. *Journal of the American Statistical Association,* *62*(318), 525–539. https://doi.org/10.1080/01621459.1967.10482926
Trinh, Q.-D. (2018). Understanding the impact and challenges of secondary data analysis. *Urologic Oncology: Seminars and Original Investigations, 36*(4), 163–164. https://doi.org/10.1016/j.urolonc.2017.11.003
Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., & Sandoval-Almazán, R. (2022). Does Twitter affect stock market decisions? Financial sentiment analysis during pandemics: A comparative study of the H1N1 and the COVID-19 periods. *Cognitive Computation,* *14*(1), 372–387. https://doi.org/10.1007/s12559-021-09819-8

Wardhani, R. S. (2022). *Mengenal saham* (V. Vebtasvili, R. I. Aprilian, & Y. Yanto, Eds.; 1st ed.). Penerbit K-Media. https://books.google.co.id/books?id=esKqEAAAQBAJ

Watson, P. K., & Teelucksingh, S. S. (2002). *A practical introduction to econometric methods: Classical and modern* (1st ed.). University of the West Indies Press. https://books.google.co.id/books?id=BU9o0QsumrUC

Waty, E., Anggraeni, A. F., Apriani, A., Ibrahim, H., Sari, A., Manafe, H. A., Juniarto, G., et al. (2023). *Metodologi penelitian bisnis: Teori & panduan praktis dalam penelitian bisnis* (1st ed.). PT. Sonpedia Publishing Indonesia. https://books.google.co.id/books?id=MVzfEAAAQBAJ

Webel, K. (2011). Greene, W. H., econometric analysis. *Statistical Papers, 52*(4).

Weerasooriya, T., Perera, N., & Liyanage, S. R. (2016). A method to extract essential keywords from a tweet using NLP tools. In *2016 Sixteenth International Conference on Advances in ICT for Emerging Regions (ICTer)* (pp. 29–34). IEEE. https://doi.org/10.1109/ICTER.2016.7829895

Yuan, K., Liu, G., Wu, J., & Xiong, H. (2020). Dancing with Trump in the stock market: A deep information echoing model. *ACM Transactions on Intelligent Systems and Technology, 11*(5). https://doi.org/10.1145/3403578

Zhong, B. (2021). *Social media communication: Trends and theories.* Wiley. https://books.google.co.id/books?id=2Ms6EAAAQBAJ