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Impact Twitter (X) Sentiment to Abnormal Return IDX30 Stocks

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Abstract

Abnormal return serves as evidence of investors' irrational behavior in response to unexpected or dramatic information. Such irrational behavior can be reflected in sentiments expressed on social media platforms such as Twitter (X). Recently, we revealed that sentiments expressed on Twitter (X) could influence stocks return rate. In this study, to analyze the effect of sentiment on Twitter (X) on stock price returns, we observed Twitter (X) sentiment and abnormal returns on IDX30 stocks. This research employs secondary data comprising 23,406 tweets related to 30 IDX30-listed stocks during the observation period fom July 2023 to December 2023. The secondary data were processed into sentiment scores and analyzed using Granger causality to examine the predictive ability of sentiment polarity on abnormal returns of IDX30 stocks. The results show that 5 out of 8 listed companies, that have causal relationship betweet positive sentiment and abnormal return, shows positive evaluation Granger Cause abnormal return. It indicated that positive sentiment could predict the abnormal return. Otherwise, 4 out 11 listed companies, that have causal relationship between negative sentiment and abnormal return, shows negative evaluation Granger Cause abnormal return. It indicated that negative sentiment is driven by abnormal returns. This research contributes to a better understanding of the Efficient Market Hypothesis in the Indonesia Stock Exchange and provides recommendation for improving the prediction of abnormal returns in the market through sentiment polarity analysis.

Keywords: Abnormal return; investor sentiment, Indonesia Stock Exchange.

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1. Introduction

Abnormal Return is a manifest form of return that deviates from the normal return. According to the Efficient Market Hypothesis (EMH) theory, stock prices reflect all available information. In other words, the magnitude of the abnormal return on a stock reflects all the available information concerning a stock issuer. Nonetheless, there exists a capital market anomaly due to the presence of irrational investors, thus the prices in the capital market may not necessarily depict all available information. Market anomalies represent observational results that are in contrast with what is expected in an efficient market (Jones & Jensen, 2016).

Social media platforms like Twitter (X) have emerged as significant channels through which market participants share their opinions, news, and sentiments regarding stocks and companies. The sentiment polarity of these posts, which can range from positive to negative, is thought to influence stock prices by affecting investors' decision-making processes. Several studies have demonstrated that sentiment analysis, particularly on Twitter, can provide insights into stock market movements (Bollen, Mao, & Zeng, 2011). Specifically, the influence of sentiment polarity on stocks listed in prominent indices such as IDX30 could potentially result in abnormal returns, as investors react to positive or negative news disseminated through these social platforms.

In conducting empirical research, researchers may employ different methods to examine the relationship between sentiment and stock return rates. For example, Hamraoui, et al (2022) utilized Twitter sentiment polarity to explore the relationship between sentiment and stock prices. Furthermore, it employed Pearson Correlation and Granger Causality to find correlation and causality relationships between sentiment polarity and abnormal returns. Baker, et al (2006) used

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proxies such as S, NIPO, RIPO, PD-ND, TURN, and CEFD to determine sentiment and its relationship with future stock returns by conducting predictive regression.

This paper contributes to the literature in the following aspects. First, inspired by Fama and French (1970) regarding efficient markets and the Efficient Market Hypothesis, where stock prices already reflect all available information. Subsequently, we developed a model to examine the influence of sentiment polarity on the abnormal returns of IDX 30 stocks, which represent issuers with large market capitalizations and are supported by strong company fundamentals. We conducted Granger Cause analysis to investigate the causal relationship between abnormal returns and sentiment polarity on Twitter (X).

As social media platforms gain influence in the financial landscape, researchers have increasingly focused on how investor sentiment expressed on platforms such as Twitter (X) affects asset prices. Bollen, et al (2011) demonstrate that aggregated mood states from Twitter can predict movements in the Dow Jones Industrial Average with considerable accuracy. Subsequent studies extend this relationship into emerging markets and sector-specific indexes. For example, Sprenger, et al (2014) find that firm-specific Twitter sentiment is significantly correlated with abnormal returns and trading volume. In the context of the Indonesian capital market, Andari and Wibowo (2021) show early evidence that public sentiment, especially during political or crisis events, tends to influence investor behavior and price volatility. Despite these findings, limited research addresses the granularity of sentiment—distinguishing between positive and negative expressions—and how they individually contribute to pricing anomalies in prominent indices like IDX30.

In the latest development, sentiment analysis has evolved into a more nuanced tool by isolating sentiment polarity (positive vs. negative tone) and linking them separately to asset behavior. Using daily Twitter data and high-frequency financial information, recent studies such as Chen, Liu, and Zhao (2023) emphasize that **positive sentiment** contributes more strongly to short-term abnormal returns, while negative sentiment tends to have a more persistent, asymmetric effect. This phenomenon aligns with behavioral finance theories, where loss aversion causes stronger reactions to negative news (Kahneman & Tversky, 1979). In the case of IDX30 stocks, initial evidence suggests that stocks with higher sensitivity to public sentiment experience greater deviation from their expected returns, especially during periods of heightened tweet volume. These findings support the view that Twitter sentiment plays a measurable and directional role in shaping excess return behavior in emerging equity markets.

This research offers two novel contributions to the literature on sentiment-based asset pricing in emerging markets. First, while previous studies (e.g., Bollen et al., 2011; Sprenger et al., 2014) have primarily focused on developed capital markets such as the U.S. and Germany, this study applies sentiment analysis to the Indonesian market by targeting IDX30 constituents—representing the most liquid stocks in the exchange. This adds new regional evidence from Southeast Asia. Second, this study disaggregates sentiment polarity into positive and negative evaluation components, thereby allowing the analysis of their separate dynamic effects on abnormal return. Compared to studies that use a net polarity score, this method enables a more granular understanding of sentiment asymmetry in return response.

The objective of this research is to examine the impact of investor sentiment on abnormal return of IDX30 stocks using Twitter (X) data. Specifically, this study aims to: (1) test whether positive and negative sentiment have statistically significant Granger-causal relationships with abnormal returns; (2) determine which sentiment polarity—positive or negative—has a more dominant influence on abnormal return variability. To achieve this, the study employs time-series econometric models such as the Vector Autoregression (VAR) framework and Granger causality tests, using panel data from multiple IDX30 firms during the selected observation period.

1.1. Problem Formulation

A previous study by Sprenger, et al (2014) examined stock-related tweets on Twitter to see whether news in the stock market had an impact on the returns of companies listed in the U.S. stock market. The results of the study showed that news events had significantly different impacts across various categories.

This phenomenon also occurred in the Indonesian capital market. One example happened at the beginning of 2022, when GoTo's stock continued to decline and became a trending topic on social media. The situation continued until the end of 2022, where GoTo was reported to have weakened due to sentiment around the Fed's interest rate policy (kumparanBISNIS, 2022).

A similar case also happened to stocks of the BAKRIE Group (BUMI, BRMS), which experienced a significant price surge in a short period of time. This was triggered by positive sentiment that went viral on social media platforms such as Twitter and online forums like Stockbit and Telegram. This was also supported by Binaartha Sekuritas analyst

Muhammad Nafan Aji Gusta, who stated that external sentiment played a role in the stock price movement of DEWA (Puspitasari, 2021).

Therefore, this study focuses on 30 stocks included in the IDX30 index on the Indonesia Stock Exchange, which are companies with high liquidity, large market capitalization, and strong fundamentals. The aim is to observe whether sentiment on social media Twitter/X has an impact on stock price changes. In addition, Indonesia ranks 4th in the world for the number of Twitter users, with 25.5 million users according to data from Katadata Media Network (Annur, 2023).

Given the large number of Twitter users in Indonesia, this study is important to answer the following questions:

1. Which factor—positive sentiment or negative sentiment—has the strongest relationship with the abnormal return of IDX30 stocks on the Indonesia Stock Exchange?
2. Does sentiment on Twitter (X) have an impact on the abnormal return of IDX30 stocks on the Indonesia Stock Exchange?

1.2. Research Objectives

The objective of this research is to explore the predictive ability of positive sentiment and negative sentiment on Twitter (X) towards investor's abnormal return in Indonesia Stock Exchange. Effendi et al (2023), examined how deceptive information ("hoaxes") spreads on Indonesian social platforms. They found that sensational headlines grab users' attenteion better than real information. It concludes that Indonesian people tend to be reactive to sensational news on social media rather than real objective news. This characteristic is interesting to test in research to see the reactions of Indonesian investors to things on social media related to the stock market. The objectives of this reasearch are:

1. To identify which factor—positive sentiment or negative sentiment—has a more dominant relationship with the abnormal returns of IDX30 stock prices on the Indonesia Stock Exchange.
2. To examine whether investor sentiment on Twitter (X) has an influence on the abnormal returns of IDX30 stocks on the Indonesia Stock Exchange.

1.3. Research Benefit

These expected benefits of this research are as follows:

1. For Investors and Listed Companies, this study provides insights into the potential influence of sentiment on Twitter (X) on the abnormal returns of Indonesian stocks. It can assist investors and investment managers in making more informed decisions by taking into account information and sentiment shared on social media.

For academics, his research is expected to offer valuable information on how investor sentiment on social media—particularly Twitter—can impact abnormal returns in the Indonesian stock market. It also aims to contribute to the body of knowledge regarding social media investor sentiment. Furthermore, it may serve as a useful reference for future studies related to investor sentiment and stock abnormal returns in Indonesia.

2. Literature Review

The foundational case for the Efficient Market Hypothesis (EMH) rests on three arguments, each based on specific assumptions. First, investors are assumed to be rational and therefore capable of valuing securities appropriately. Second, when some investors behave irrationally, their trading activities are presumed to be random and thus cancel each other out, leaving prices unaffected. Third, if irrational investors share the same biases, their influence on prices will be offset by rational arbitrageurs in the market, thereby eliminating any price distortion (Shleifer A. , 2000).

However, several studies have identified the presence of anomalies in the stock market that are attributed to irrational investor behavior. Market anomalies refer to empirical observations that deviate from the expectations of an efficient market (Jones & Jensen, 2016). One such anomaly arises from psychological behavior, commonly referred to as behavioral finance. This theory suggests that investors are prone to systematic errors in their financial decision-making. These investors are influenced by various "irrational" forces; meanwhile, other market participants recognize these decision-making anomalies and seek to exploit the resulting opportunities (Jones & Jensen, 2016).

A key milestone in the development of behavioral finance stems from the study by DeBondt and Thaler (1985), which examined the "overreaction hypothesis." This hypothesis posits that individuals tend to overreact to unexpected and

dramatic events. In the context of stock prices, such overreaction implies that portfolios consisting of previously underperforming (loser) stocks tend to outperform the market after their formation. DeBondt and Thaler interpreted these findings as evidence of irrational investor behavior, commonly referred to as "overreaction".

2.1. Abnormal Return

Abnormal return refers to the difference between the actual return received by investors and the expected normal return under efficient market conditions. This return arises within a specific time frame and reflects the market's reaction to a particular event (Hartono, 2017).

Studies on abnormal return are generally conducted using an event study methodology, which analyzes market responses before and after the announcement of significant events. Abnormal returns are often observed during specific periods, such as national holidays, the beginning of a month or year, political regime changes, stock splits, initial public offerings (IPOs), or other extraordinary occurrences.

Abnormal return is defined as the difference between the actual realized return and the expected return (Hartono, 2017). The abnormal return for stock i on day t can be calculated using the following formula:

$$AR_{it} = R_{it} - ER_{it} \quad (1)$$

Where: AR_{it} is stock abnormal return i on day-t, R_{it} is stock actual return i on day-t, ER_{it} is stock expected return i on day-t.

2.2. Investor Sentiment

Sentiment is a way to express someone's view, opinion, or belief about a certain thing. In finance, investor sentiment means how investors feel or what they believe about the possible return and risk of a stock in the future. These beliefs might not always be correct (Baker & Wurgler, 2006). A sentiment is called optimistic if it includes positive words like success, efficient, increase, or profit. On the other hand, a pessimistic sentiment uses negative words such as failure, inefficiency, decrease, or loss (Loughran & Mc Donald, 2011).

There are several methods available to measure investor sentiment. Baker and Wurgler (2007) highlighted different ways to capture investor sentiment, such as investor surveys, investor mood, trading activity by retail investors, mutual fund flows, trading volume, dividend premiums, closed-end fund discounts, option volatility, first-day returns of initial public offerings (IPOs), IPO volume, the ratio of equity issuance to new equity, and insider trading. However, as more people spend their time sharing and reading opinions on social media, investor sentiment measurement has also developed to include analysis from platforms like Twitter, Wikipedia, and Google search trends (Leitch & Sherif, 2017).

Twitter is one of the most popular social media platforms today. By using tweets, or status updates, Twitter makes it possible to analyze public opinion and sentiment by looking at tweet conversations to predict certain behaviors. Even though each tweet only shows one person's view and is limited to 140 characters, all the tweets together can give an accurate picture of the overall mood and general sentiment (Sun, 2016; Nisar & Yeung, 2018).

3. Methods

To explore the relationship betweet Twitter (X) sentiment and abnormal returns, we apply the Granger causality tests. We use Granger causality test to check wheter the Positive Evaluation (PE) and Negative Evaluation (NE) on Twitter (X) help predict stock abnormal return. The steps of the estimation procedure are summarized as follows (Hamraoui & Boubaker, 2022;Zhang, Wang, Guo, & Zhang, 2018):

- Determine whether the two-time series are non-stationary, using Augmented Dickey-Fuller (ADF) test and Philipp Perron (PP) tests.
- Build a Vector Autoregressive (VAR) model and determine its optimal order by considering three measures: AIC, SC, HQ.
- Fit the VAR model with the selected order from the previous step.
- Perform the Granger causality test

3.1. Market Data

The market data used in this study comes from companies listed on the Indonesia Stock Exchange (IDX) and included in the IDX30 index. These companies are: ADRO, AKRA, AMRT, ANTM, ARTO, ASII, BBCA, BBNI, BBRI, BMRI, BRPT, BUKA, CPIN, EMTK, ESSA, GOTO, HRUM, INCO, INDF, ITMG, KLBF, MDKA, MEDC, PGAS, PTBA, SMGR, TLKM, TOWR, UNTR, and UNVR. The observation period was set for 6 months, from July 1, 2023, to December 31, 2023.

The companies' accounting and financial data were collected from the Indonesia Stock Exchange database. For each share, we determine a time series of abnormal returns with equation in formula 1.

3.2. Twitter Data

The second data source is social media data from Twitter (X), which includes all tweets related to IDX30 listed companies and their associated sentiment. The data was collected through a scraping process using the names of IDX30 companies as keywords, covering the period from July 2023 to December 2023 (Go, Bhayani, & Huang, 2009). All tweets, including replies and retweets, were counted as one sentiment.

In addition, Twitter (X), as the platform owner, has implemented policies that prohibit phishing and spam practices, including the use of automated accounts (bots) that spread harmful links or manipulative content (X, 2025). Twitter (X) also takes enforcement actions if it detects violations, either through its automatic detection system or through user reports, as explained on its official website: https://help.x.com/en/rules-and-policies/authenticity.

Therefore, the tweets collected through scraping in this study are free from spam or phishing tweets that include stock ticker keywords. The scraped text data was then analyzed using the lexicon method (lexicon-based sentiment analysis), which is an approach that uses a dictionary of words (lexicon) categorized into positive, negative, and neutral sentiment.

As in the study by Zhang, et al (2018), sentiment on Twitter (X) was calculated by counting the positive and negative emotional index. The emotional index is calculated by using the ratio of the number of tweets on one day's positive evaluation (or negative evaluation) and the total number of tweets on the day. Computational formula are as follows:

$$posindex_t = \frac{poscount_t}{total_t} \tag{2}$$

$$negindex_t = \frac{negcount_t}{total_t} \tag{3}$$

Where $posindex_t$ is positive index in day-t, $poscount_t$ is positve tweet count in day-t, $negindex_t$ is negative index in day-t, $negcount_t$ is negative tweet count in day-t, and $total_t$ is total tweet (positive, negative, and neutral) in day-t. From this observation process we get 23,406 tweets in total with details on table 1.

In the context of daily sentiment analysis, if no tweet data is found for a particular stock on a given day, the sentiment polarity value for that day is assumed to be zero (0). This represents a neutral condition without any market opinion pressure. With this approach, the time series data structure remains complete, allowing analyses such as the VAR model, Granger causality test, or panel regression to be performed without being affected by missing data.

Table 1. IDX30 stock issuer tweet distribution July 2023 – December 2023

Saham	Positive_Tweet	Negative_Tweet	Neutral_Tweet	Total_Tweet
ADRO	130	147	155	432
AKRA	180	110	174	464
AMRT	67	44	77	188
ANTM	224	155	162	541
ARTO	364	235	299	898
ASII	293	276	690	1259

Saham	Positive_Tweet	Negative_Tweet	Neutral_Tweet	Total_Tweet
BBCA	193	252	257	702
BBNI	253	180	246	679
BBRI	206	179	245	630
BMRI	357	351	360	1068
BRPT	349	220	324	893
BUKA	18	17	21	56
CPIN	76	51	74	201
EMTK	60	40	75	175
ESSA	19	47	46	112
GOTO	252	292	217	761
HRUM	105	48	77	230
INCO	85	55	116	256
INDF	67	51	51	169
ITMG	145	147	149	441
KLBF	66	59	76	201
MDKA	106	70	104	280
MEDC	242	155	369	766
PGAS	123	124	136	383
PTBA	258	285	218	761
SMGR	115	51	117	283
TLKM	1014	697	671	2382
TOWR	58	51	73	182
UNTR	222	206	220	648
UNVR	192	322	154	668

3.3. Granger Causality

To test the causal relationship between the three variables—Positive Evaluation (PE), Negative Evaluation (NE), and abnormal return of IDX30 stocks—this study uses the Granger Causality Test. Granger causality is used to test whether one variable can help predict another variable based on its historical data. This model allows for testing bidirectional predictive relationships between all combinations of variables.

The VAR (Vector Autoregression) model, as explained earlier, is a linear simultaneous model where each endogenous variable is modeled as a function of its own lagged values and the lagged values of all other variables in the system. For a three-variable VAR with lag p, the system of equations is as follows:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_j X_{t-j} + \varepsilon_t \quad (4)$$

In this model, Y_t represents a k-dimentional vector of endogenous variables, while Y_{t-1} denotes the lagged vector of endogenous variables. X_{i-t} stands for the lagged values of a d-dimensional exogenous variable. The terms *p* and *r* indicate te lag orders of the endogenous and exogenous variables, respectively. α_i is a *k* x *k* coefficient matrix, β_j is a *k* x *d* coefficient matrix, and ε_t is a k-dimensional vector representing the error or disturbance term.

If the probability value (p-value) from the F-statistic test is smaller than the significance level, it means there is a Granger causal relationship between the variables.

4. Result and Discussions

4.1. Descriptive Statistical Analysis

his study conducted a descriptive statistical analysis to examine the distribution and characteristics of the three key variables: Positive Evaluation, Negative Evaluation, and Abnormal Return. The results are summarized in Table 2.

Table 2. Descriptive Statistical Analysis Results for IDX30 Stocks

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis
Positive_Evaluation	0.26465	0.2	1	0	0.30590	1.01022	0.10996
Negative_Evaluation	0.23117	0.09090	1	0	0.29608	1.24172	0.69485
Abnormal_Return	-0.01960	-0.02342	0.24645	-0.18504	0.02916	1.37945	7.18261

The Positive Evaluation variable, which reflects the proportion of positive sentiment from Twitter (X) related to IDX30 stocks, has a mean value of 0.26465 and a median of 0.2. The data is positively skewed (skewness = 1.01022), indicating that most observations are concentrated at lower values, with a few higher outliers. The standard deviation is 0.3059, suggesting moderate variability. The kurtosis value of 0.10996 implies a distribution that is relatively flat compared to the normal distribution.

Similarly, the Negative Evaluation variable shows a mean of 0.23117 and a median of 0.0909. The positive skewness (1.24172) and relatively low median value suggest that negative sentiment scores are also mostly concentrated at lower values, with occasional high spikes. The standard deviation is 0.29608, and the kurtosis of 0.69485 indicates a somewhat light-tailed distribution.

In contrast, the Abnormal Return variable displays different characteristics. It has a mean of -0.0196 and a median of -0.02342, indicating a slight overall tendency for stock returns to fall below expected values during the observation period. The skewness of 1.37945 indicates a right-skewed distribution, with more frequent small losses and a few extreme positive returns. The kurtosis value of 7.18261 suggests a leptokurtic distribution, meaning that the data has heavier tails than the normal distribution—an indication of the presence of outliers or extreme events in the stock return data. The relatively low standard deviation of 0.0292 reflects limited variability in daily abnormal returns.

These descriptive insights support the notion that sentiment variables derived from social media tend to be sparse or extreme, while abnormal return data may contain sharp deviations that warrant further modeling using time-series and causal inference techniques.

4.2. Stationary Test

Before conducting the Granger causality analysis, it is necessary to perform a stationarity test to ensure that the data is suitable for further analysis. Stationarity is required to determine the optimal lag length in the VAR model and to proceed with the Granger causality testing.

Table 3. ADF Stationary Test for AR,PE, and NE

Saham	ADF_Abnormal_Return	ADF_Positive_Evaluation	ADF_Negative_Evaluation
ADRO	0.01	0.01	0.01
AKRA	0.01	0.01	0.01
AMRT	0.01	0.01	0.01
ANTM	0.01	0.01	0.021065492
ARTO	0.01	0.01	0.01
ASII	0.01	0.01	0.01
BBCA	0.01	0.012829111	0.01
BBNI	0.01	0.01	0.01

Saham	ADF_Abnormal_Return	ADF_Positive_Evaluation	ADF_Negative_Evaluation
BBRI	0.01	0.027145328	0.01
BMRI	0.01	0.01	0.01
BRPT	0.01	0.013553736	0.01
BUKA	0.01	0.01	0.01
CPIN	0.01	0.01	0.01
EMTK	0.012075441	0.01	0.01
ESSA	0.01	0.01	0.01
GOTO	0.01	0.019560296	0.01
HRUM	0.01	0.01	0.01
INCO	0.01	0.043863434	0.033489308
INDF	0.01	0.01	0.01
ITMG	0.01086294	0.01	0.01
KLBF	0.01	0.01	0.01
MDKA	0.01	0.01	0.01
MEDC	0.01	0.01	0.01
PGAS	0.01	0.01	0.01
PTBA	0.01	0.01	0.040028591
SMGR	0.01	0.01	0.01
TLKM	0.01	0.01	0.01
TOWR	0.01	0.01	0.01
UNTR	0.01	0.01	0.01
UNVR	0.01	0.01	0.01

In this study, the Augmented Dickey-Fuller (ADF) test was applied to each stock time series. As shown in Table 3, all stocks produced p-values less than 0.05 for both variables, indicating that all time series data are stationary. This satisfies the prerequisite for proceeding with the analysis of optimal lag selection in the VAR model and the Granger Causality test to examine the dynamic relationships among abnormal return, positive evaluation, and negative evaluation.

4.3. Determination of Lag Order

We refer to the modified SCHWARTZ criterion (SC), the AKAIKE criterion (AIC), and the Hannan-Quinn criterion (HQ), assumed to be efficient, in addition to the log likelihood to determine lag order of (VAR) models. Table 4 show the optimum lag order based on that SC, AIC, and HQ criteria.

Table 4. Determination of optimum lag order

Stock	**Criteria**	**lag_1**	**lag_2**	**lag_3**	**lag_4**	***lag_select***
ADRO	AIC	**-12.835944***	-12.808496	-12.780795	-12.719275	1
	SC	**-12.558676***	-12.323276	-12.087624	-11.818152	
	HQ	**-12.723335***	-12.61143	-12.499272	-12.353295	
AKRA	AIC	**-13.47301***	-13.384314	-13.357626	-13.324162	1
	SC	**-13.195741***	-12.899094	-12.664455	-12.423039	
	HQ	**-13.3604***	-13.187248	-13.076103	-12.958181	
AMRT	AIC	**-12.536511***	-12.499607	-12.483574	-12.425964	1
	SC	**-12.259242***	-12.014387	-11.790402	-11.524842	
	HQ	**-12.423902***	-12.302541	-12.20205	-12.059984	

Stock	Criteria	lag_1	lag_2	lag_3	lag_4	*lag_select*
ANTM	AIC	**-13.619693***	-13.542145	-13.439365	-13.322959	1
	SC	**-13.342425***	-13.056925	-12.746194	-12.421836	
	HQ	**-13.507084***	-13.345078	-13.157842	-12.956978	
ARTO	AIC	**-12.172216***	-12.108568	-12.014174	-11.890369	1
	SC	**-11.894948***	-11.623348	-11.321003	-10.989247	
	HQ	**-12.059607***	-11.911502	-11.732651	-11.524389	
ASII	AIC	**-16.643618***	-16.542061	-16.458898	-16.360053	1
	SC	**-16.366349***	-16.056841	-15.765727	-15.458931	
	HQ	**-16.531008***	-16.344994	-16.177375	-15.994073	
BBCA	AIC	**-14.220272***	-14.130132	-14.0501	-14.024243	1
	SC	**-13.943004***	-13.644912	-13.356929	-13.12312	
	HQ	**-14.107663***	-13.933066	-13.768576	-13.658262	
BBNI	AIC	-14.312885	**-14.317223***	-14.246249	-14.203933	1
	SC	**-14.035616***	-13.832003	-13.553078	-13.302811	
	HQ	**-14.200275***	-14.120157	-13.964726	-13.837953	
BBRI	AIC	**-14.152065***	-14.077347	-14.014977	-13.9358	1
	SC	**-13.874796***	-13.592127	-13.321805	-13.034678	
	HQ	**-14.039455***	-13.880281	-13.733453	-13.56982	
BMRI	AIC	**-15.786942***	-15.704738	-15.579994	-15.603821	1
	SC	**-15.509674***	-15.219518	-14.886823	-14.702698	
	HQ	**-15.674333***	-15.507672	-15.298471	-15.237841	
BRPT	AIC	**-11.559019***	-11.519379	-11.422568	-11.296928	1
	SC	**-11.281751***	-11.034159	-10.729397	-10.395805	
	HQ	**-11.44641***	-11.322313	-11.141045	-10.930947	
BUKA	AIC	**-12.231465***	-12.182803	-12.118809	-12.116254	1
	SC	**-11.954197***	-11.697583	-11.425638	-11.215132	
	HQ	**-12.118856***	-11.985737	-11.837286	-11.750274	
CPIN	AIC	**-12.036289***	-11.944255	-11.885874	-11.816526	1
	SC	**-11.75902***	-11.459036	-11.192703	-10.915403	
	HQ	**-11.923679***	-11.747189	-11.604351	-11.450546	
EMTK	AIC	**-11.961708***	-11.880576	-11.864378	-11.766414	1
	SC	**-11.684439***	-11.395356	-11.171206	-10.865291	
	HQ	**-11.849099***	-11.68351	-11.582854	-11.400434	
ESSA	AIC	**-11.426276***	-11.350539	-11.328867	-11.23004	1
	SC	**-11.149007***	-10.86532	-10.635696	-10.328918	
	HQ	**-11.313666***	-11.153473	-11.047344	-10.86406	
GOTO	AIC	**-11.523123***	-11.481232	-11.365332	-11.269243	1
	SC	**-11.245855***	-10.996012	-10.672161	-10.36812	
	HQ	**-11.410514***	-11.284166	-11.083809	-10.903262	
HRUM	AIC	**-11.925257***	-11.843523	-11.760554	-11.759961	1
	SC	**-11.647989***	-11.358303	-11.067382	-10.858838	
	HQ	**-11.812648***	-11.646457	-11.47903	-11.393981	

Stock	Criteria	lag_1	lag_2	lag_3	lag_4	*lag_select*
INCO	AIC	**-14.228987***	-14.22148	-14.196501	-14.208365	1
	SC	**-13.951719***	-13.73626	-13.50333	-13.307242	
	HQ	**-14.116378***	-14.024414	-13.914978	-13.842385	
INDF	AIC	**-13.271504***	-13.207495	-13.114878	-13.086859	1
	SC	**-12.994236***	-12.722275	-12.421706	-12.185737	
	HQ	**-13.158895***	-13.010429	-12.833354	-12.720879	
ITMG	AIC	**-13.229507***	-13.131922	-13.019425	-12.934604	1
	SC	**-12.952239***	-12.646702	-12.326254	-12.033482	
	HQ	**-13.116898***	-12.934855	-12.737902	-12.568624	
KLBF	AIC	**-12.300054***	-12.292366	-12.181789	-12.12935	1
	SC	**-12.022785***	-11.807146	-11.488618	-11.228228	
	HQ	**-12.187444***	-12.095299	-11.900266	-11.76337	
MDKA	AIC	**-11.61839***	-11.525696	-11.433252	-11.372509	1
	SC	**-11.341121***	-11.040476	-10.740081	-10.471387	
	HQ	**-11.505781***	-11.32863	-11.151729	-11.006529	
MEDC	AIC	**-13.10323***	-13.026203	-13.03921	-12.944175	1
	SC	**-12.825962***	-12.540983	-12.346039	-12.043052	
	HQ	**-12.990621***	-12.829137	-12.757687	-12.578195	
PGAS	AIC	**-13.155762***	-13.108788	-13.08495	-13.043133	1
	SC	**-12.878494***	-12.623568	-12.391779	-12.142011	
	HQ	**-13.043153***	-12.911722	-12.803427	-12.677153	
PTBA	AIC	**-14.252256***	-14.230909	-14.156508	-14.102357	1
	SC	**-13.974987***	-13.745689	-13.463337	-13.201234	
	HQ	**-14.139646***	-14.033843	-13.874985	-13.736376	
SMGR	AIC	**-12.699816***	-12.661276	-12.561387	-12.524301	1
	SC	**-12.422547***	-12.176056	-11.868216	-11.623178	
	HQ	**-12.587207***	-12.46421	-12.279864	-12.158321	
TLKM	AIC	**-15.447062***	-15.401981	-15.318747	-15.284042	1
	SC	**-15.169794***	-14.916761	-14.625576	-14.382919	
	HQ	**-15.334453***	-15.204914	-15.037224	-14.918062	
TOWR	AIC	**-12.505153***	-12.369473	-12.317256	-12.325535	1
	SC	**-12.227885***	-11.884253	-11.624085	-11.424412	
	HQ	**-12.392544***	-12.172407	-12.035733	-11.959555	
UNTR	AIC	**-13.858653***	-13.79255	-13.70364	-13.621383	1
	SC	**-13.581385***	-13.30733	-13.010469	-12.72026	
	HQ	**-13.746044***	-13.595483	-13.422117	-13.255403	
UNVR	AIC	**-13.065752***	-13.003459	-12.870573	-12.838991	1
	SC	**-12.788483***	-12.518239	-12.177402	-11.937868	
	HQ	**-12.953142***	-12.806392	-12.58905	-12.47301	

Table 4 shows that the optimal lag for all observed stocks is 1. This indicates that the model performs efficiently at lag 1.

4.4. Granger Causality Test

The Granger causality test was conducted to evaluate the causal relationships between positive sentiment, negative sentiment on Twitter (X), and abnormal return for each stock in the IDX30 index. This test was performed using daily time series data while considering the stationarity of the variables.

The results indicate a diverse pattern of causal relationships among the variables for each stock. Some stocks exhibit bidirectional causality, while others show only unidirectional relationships or no significant relationship at all.

Table 5. Granger Causality Test on variables PE, NE, and AR

Stocks	PE→AR		AR→PE		NE→AR		AR→NE	
	F-Stat	**P-Val**	**F-Stat**	**P-Val**	**F-Stat**	**P-Val**	**F-Stat**	**P-Val**
ADRO	6.9296	**0.0096*** **	2.5556	0.1125	1.9712	0.1629	2.2678	0.1347
AKRA	0.1149	0.7352	0.4252	0.5156	0.0006	0.9798	3.0315	**0.0842***
AMRT	0.024	0.8771	1.9229	0.1681	0.2952	0.5879	0.1982	0.657
ANTM	0.4557	0.5009	0.1751	0.6764	0.0172	0.896	0.1937	0.6606
ARTO	1.772	0.1856	0.5255	0.4699	3.4868	**0.0643***	0.1025	0.7494
ASII	5.5344	**0.0203** **	0.2606	0.6107	0.0373	0.8472	0.0056	0.9406
BBCA	0.1406	0.7084	0.9099	0.342	0.9209	0.3392	2.7944	**0.0972***
BBNI	1.0017	0.3189	2.7136	0.1021	3.4241	**0.0667***	0.3796	0.539
BBRI	1.1774	0.2801	0.1515	0.6978	0.1584	0.6914	3.9165	**0.0501***
BMRI	0.6507	0.4214	1.1234	0.2913	0.1127	0.7377	2.7965	**0.0971***
BRPT	0.12	0.7296	0.1193	0.7304	0.0595	0.8078	0.0005	0.9818
BUKA	0.8459	0.3595	0.1303	0.7187	0.0614	0.8047	0.6831	0.4102
CPIN	0.0651	0.7991	3.5091	**0.0634***	0.0456	0.8313	1.4144	0.2367
EMTK	0.8316	0.3636	0.9651	0.3279	1.9531	0.1648	1.1356	0.2887
ESSA	3.3084	**0.0714***	1.2224	0.2711	3.0793	**0.0818***	0.5931	0.4427
GOTO	1.94	0.1662	0.976	0.3252	0.3826	0.5374	1.9917	0.1607
HRUM	2.9514	**0.0884***	0.292	0.5899	0.3594	0.55	11.5329	**0.0009*** **
INCO	5.8355	**0.0172** **	0.1493	0.6999	0.0442	0.8337	0.0008	0.9782
INDF	1.8967	0.171	0.2385	0.6262	0.1484	0.7008	0.0347	0.8526
ITMG	0.8403	0.3611	5.1824	**0.0246** **	7.7598	**0.0062*** **	1.2197	0.2716
KLBF	0	0.9965	0.0065	0.9361	0.0032	0.9551	0.7815	0.3784
MDKA	0.0007	0.979	0.4205	0.5179	0.1766	0.675	0.4027	0.5269
MEDC	1.0344	0.3112	1.0389	0.3101	1.9127	0.1692	3.1752	**0.0773***
PGAS	0.0106	0.9181	2.6298	0.1075	1.5416	0.2168	1.8777	0.1731
PTBA	0.0727	0.7879	0.1266	0.7226	0.0191	0.8902	0.0396	0.8425
SMGR	0.3166	0.5747	9.0011	**0.0033*** **	0.0488	0.8256	1.0204	0.3144
TLKM	0.9372	0.3349	0.6083	0.4369	0.2896	0.5915	0.6219	0.4319
TOWR	0.7297	0.3947	0.853	0.3575	0.3276	0.5681	1.7354	0.1902
UNTR	0.1567	0.6929	1.9259	0.1678	0.0965	0.7566	2.9436	**0.0888***
UNVR	0.3769	0.5404	0.4778	0.4907	0.2521	0.6165	0.1798	0.6723

Based on the data analysis, it can be observed that positive evaluation (positive sentiment) is essential for 26.7% of the companies in the IDX30 index, with the following details:

a. The stocks ADRO, ASII, ESSA, HRUM, and INCO show that positive evaluation Granger-causes abnormal return, with p-values of 0.0096***, 0.0203**, 0.00714***, 0.0884*, and 0.0172**, respectively.

b. The stocks CPIN, ITMG, and SMGR indicate that abnormal return Granger-causes positive evaluation, with p-values of 0.0634*, 0.0246**, and 0.0033***.

Out of the eight stocks with significant p-values, five demonstrate a causal relationship from positive evaluation to abnormal return. These findings differ from the earlier sentiment polarity analysis, suggesting that in the Indonesian stock market, positive sentiment can serve as a predictive factor for abnormal returns. Positive sentiments expressed on Twitter may act as early indicators that investors could gain abnormal returns when investing in those particular stocks.

In addition to positive evaluation, a Granger causality test was also conducted on negative evaluation (negative sentiment). As shown in Table 4.13, negative evaluation is essential for 36.7% of the IDX30 companies, with the following details:

a. The stocks ARTO, BBNI, ESSA, and ITMG show that negative evaluation Granger-causes abnormal return, with p-values of 0.0643*, 0.0667*, 0.0818*, and 0.0062***.

b. The stocks AKRA, BBCA, BBRI, BMRI, HRUM, MEDC, and UNTR indicate that abnormal return Granger-causes negative evaluation, with p-values of 0.0842*, 0.0972*, 0.0501*, 0.0971*, 0.0009***, 0.0773*, and 0.0888*, respectively.

Of the eleven stocks with significant p-values, only four show a causal relationship from negative evaluation to abnormal return. This suggests that the Indonesian stock market tends to be reactive in responding to negative sentiment related to listed stocks.

Overall, these findings indicate that the impact of social media sentiment on abnormal return appears only in certain IDX30 stocks, and the influence is selective and temporary. This is consistent with the findings of Hamraoui & Boubaker (2022), who noted that sentiment effects do not occur across all stocks, but rather in those with specific characteristics such as high media exposure or mid-sized market capitalization.

5. Conclusions

This study aims to identify which factor positive sentiment or negative sentiment—has a more dominant relationship with abnormal return in IDX30 stocks in Indonesia during the research period from July to December 2023. The results of the Granger causality analysis show that only 8 issuers (26.7%) exhibit a significant relationship between positive sentiment and abnormal return, while 11 issuers (36.7%) show a relationship between negative sentiment and abnormal return. These findings indicate that negative sentiment has a more significant influence on abnormal return in the Indonesian stock market compared to positive sentiment.

This study also further analyzes the predictive power of sentiment on abnormal return. It was found that 5 out of the 8 issuers with a causal relationship between positive sentiment and abnormal return demonstrated a predictive influence on abnormal return. This suggests that positive sentiment in the Indonesian stock market may serve as an early signal of potential abnormal returns for investors. In contrast, among issuers with a significant relationship between negative sentiment and abnormal return, only 4 out of 11 demonstrated predictive power. This implies that negative sentiment in the Indonesian stock market reflects more of a reactive response from investors rather than a predictive one.

Based on the findings of this study, several recommendations can be proposed to support investment decision-making in the Indonesian stock market. Investors and issuers should consider positive sentiment as an additional input when making investment decisions. Meanwhile, negative sentiment should be used by companies as an early warning indicator to take proactive corporate actions or damage control measures before investor reactions escalate. These results can also help academics gain a deeper understanding of the behavioral characteristics of the Indonesian stock market.

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