Research Article

NAVIGATING MARKET VOLATILITY: THE ROLE OF INVESTOR SENTIMENT AND LIQUIDITY IN INDONESIA'S CAPITAL MARKET, 2011–2025

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ABSTRACT

Background: Stock market volatility reflects not only macroeconomic fundamentals but also investor sentiment and market liquidity. Although investor sentiment is widely recognized as a potential driver of volatility, its effects may depend on prevailing liquidity conditions. This interaction is particularly relevant in emerging markets, where investor behavior and trading activity may jointly shape price fluctuations.
Purpose: This study examines the effects of positive and negative investor sentiment on Jakarta Composite Index (IHSG) return volatility, with particular attention to the moderating role of market liquidity.
Design/methodology/approach: The study uses monthly time-series data from January 2011 to December 2025. Investor sentiment indices are constructed using Google Search Trends, while the turnover ratio serves as a proxy for market liquidity and the moderating variable. An autoregressive distributed lag error correction model (ARDL-ECM) is employed to examine short-run and long-run relationships among investor sentiment, market liquidity, macroeconomic factors, and IHSG return volatility.
Findings/Results: The findings indicate that both positive and negative investor sentiment significantly increase IHSG return volatility when modeled separately. However, when both sentiments are incorporated into a single model, only negative investor sentiment has a statistically significant effect. The turnover ratio also exhibits a positive and significant effect on volatility across all model specifications. When estimated separately, its moderating effects vary across sentiment dimensions, with higher liquidity attenuating the volatility effect of positive sentiment, whereas lower liquidity amplifies the effect of negative sentiment. However, when both sentiment measures are included simultaneously, market liquidity no longer exhibits a significant moderating effect on either positive or negative sentiment.
Conclusion: Overall, negative sentiment exhibits greater explanatory power, while market liquidity consistently increases volatility. However, liquidity does not significantly moderate sentiment effects when both sentiments are considered simultaneously.
Originality/value (State of the art): This study integrates investor sentiment, market liquidity, and macroeconomic factors into a unified framework for explaining stock market volatility in Indonesia. Its main contribution is to demonstrate that market liquidity is not merely associated with the level of volatility but also conditions how investor sentiment translates into market fluctuations. By distinguishing the effects of positive and negative sentiment, the study provides a more nuanced understanding of the sentiment–liquidity–volatility nexus in an emerging market.

ARTICLE INFO

Keywords:
ARDL-ECM, Google Search Trends, IHSG, return volatility, turnover ratio

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INTRODUCTION

Capital markets are a key component of the financial system, facilitating the allocation of funds while linking domestic markets to the global financial system through economic conditions, monetary policy, and cross-border capital flows. In emerging economies such as Indonesia, the capital market serves not only as an alternative source of corporate financing but also as an important indicator of economic stability and investor confidence. The Jakarta Composite Index (IHSG) captures the interplay of economic fundamentals, market structure, and investor behavior in the price formation process. Consequently, IHSG

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movements are driven not only by macroeconomic conditions and corporate performance but also by market mechanisms and liquidity (Kyle, 1985), as well as investor sentiment, expectations, and responses to information (Baker & Wurgler, 2007). These dynamics are evident in the substantial fluctuations of the IHSG from 2011 to 2025, highlighting the need to examine how market liquidity and investor sentiment jointly shape stock return volatility (Figure 1).

Market volatility tends to rise as liquidity weakens, increasing the likelihood that price shocks will amplify. Previous studies find a significant inverse relationship between liquidity and volatility and show that heightened volatility can reduce liquidity and increase transaction costs (Muzaffar & Malik, 2024). This mechanism is particularly relevant in emerging markets such as Indonesia, which are more sensitive to global shocks and uncertainty (Hashmi et al. 2021). The pronounced IHSG fluctuations from 2011 to 2025, particularly during the 2013 tapering episode, the 2018 to 2019 US–China trade tensions, and the COVID-19 pandemic, further highlight the market's vulnerability to global and domestic shocks (Sahay et al. 2014a; Baker et al. 2020). However, the relationship between liquidity and volatility may also depend on investor behavior and prevailing market conditions, suggesting that liquidity alone may not fully explain fluctuations in stock returns.

Indonesia's stock market has experienced growing retail investor participation, particularly among younger investors. As of December 2025, investors aged 30 or below accounted for 54.24% of total investors (KSEI, 2025), highlighting the increasing role of younger generations in trading and price formation. In this context, investor sentiment becomes increasingly relevant as it captures expectations about risk and future price movements and shapes collective responses to market information (Baker & Wurgler, 2007). Sentiment may manifest through optimism, euphoria, or fear, influencing investment decisions and short-term market dynamics (Wang, 2024). From a behavioral finance perspective, these psychological factors may trigger collective behaviors such as herding and overreaction, which can amplify stock market volatility (Yi, 2024). Investor sentiment may also affect trading activity and short-term market liquidity, further highlighting the importance of examining sentiment and liquidity jointly in explaining market fluctuations (Enow et al. 2022).

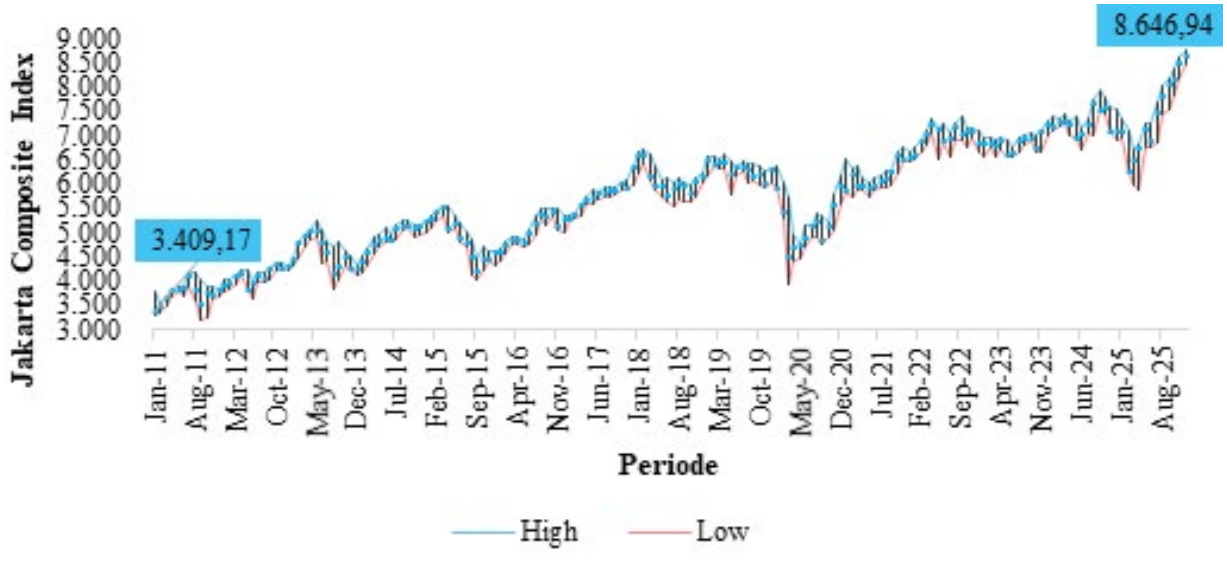


Figure 1. Historical Data of the Jakarta Composite Index (IHSG) (Yahoo Finance, 2026)

Recent studies increasingly use digital indicators to capture investor attention and uncertainty. Szczygielski et al. (2024) find that Google search trends related to stock markets reflect uncertainty and are associated with lower market returns and higher volatility across countries. Similarly, evidence from Google Search Volume Index indicates that changes in investor attention are linked to market returns, volatility, and trading volume, although the effects vary across countries and periods (Ayala et al. 2024; Szczygielski et al. 2024). These findings highlight investor sentiment and attention as important factors in understanding stock market volatility in rapidly evolving information environments. Following the Loughran–McDonald Dictionary and prior studies (Mao et al. 2011; Da et al. 2015; Brochado, 2020; Ballinari & Behrendt, 2021), this study constructs positive and negative sentiment indices using market-relevant keywords adapted to the Indonesian context following Gao et al. (2015). Positive sentiment is captured by searches for IPO, economic growth, rising stocks, and dividends, while negative sentiment is measured through searches for falling stocks, economic crisis, bankruptcy, and layoffs. Meanwhile, digitalization and rising retail participation have contributed to the development of Indonesia's capital market and increased trading activity (KSEI, 2026; Rohyati et al. 2024). Although greater liquidity can improve price discovery and reduce transaction costs, its effect on market stability is not necessarily linear, as liquidity may either absorb or amplify shocks depending on investor composition and market conditions (haritha & Thomadakis, 2024; Wooldridge, 2020). Empirical evidence on the liquidity and volatility relationship remains mixed. While higher liquidity may reduce volatility by facilitating transactions with limited price impact (Muzaffar & Malik, 2024), changes in trading activity and market conditions may also coincide with increased volatility. Similarly, previous studies find that investor sentiment can increase market volatility, although its effects may vary across market conditions and types of sentiment (Widhiarti et al. 2018; Zunara et al. 2022; Ernawati et al. 2022). These findings raise an important question of whether market liquidity strengthens market resilience or changes the extent to which sentiment-driven trading affects stock market volatility.

Despite growing interest in investor sentiment and market liquidity, previous studies have largely examined their relationships with stock market volatility separately. Empirical evidence suggests that investor sentiment, driven by psychological factors and market news, can significantly affect stock market volatility through irrational trading behaviors such as herding and overreaction (Goolam et al. 2025). Similarly, sentiment indices have been shown to significantly influence stock market volatility, particularly in emerging markets (Haritha & Rishad, 2020). Market liquidity and depth are also closely associated with volatility, as less liquid markets tend to experience sharper price movements under demand or selling pressures (Meldrum & Sokolinskiy, 2025). However, evidence on the interaction between investor sentiment and market liquidity in explaining IHSG volatility remains limited, particularly regarding the moderating role of market liquidity and the potential differences between positive and negative sentiment. This gap is particularly relevant in Indonesia, where growing retail investor participation and the use of digital search indicators provide an opportunity to examine how sentiment and liquidity jointly shape market volatility.

This study extends prior Indonesian evidence by examining the effects of positive and negative investor sentiment on IHSG return volatility, both separately and jointly, while explicitly considering the moderating role of market liquidity. Using Google Search Trends to construct investor sentiment indices and the turnover ratio as a proxy for market liquidity, this study addresses three research questions: (1) Do positive and negative investor sentiment affect IHSG return volatility?, (2) Does market liquidity moderate the relationship between each type of sentiment and volatility?, and (3) Do these effects differ when both sentiment measures are examined simultaneously?. By incorporating interaction terms and conducting marginal effect analysis, this study provides a more comprehensive understanding of how market liquidity shapes the relationship between investor sentiment and stock market volatility in Indonesia. This approach also helps identify potential differences in the moderating effects of liquidity across positive and negative sentiment.

METHODS

This study uses monthly secondary time-series data spanning January 2011 to December 2025. The dependent variable is the Jakarta Composite Index (IHSG) return, which is further transformed to obtain

return volatility. The explanatory variables include the turnover ratio, derived from transaction value and market capitalization, and eight Google Search Trends (GST) keyword indices aggregated into positive and negative sentiment indices. The model also incorporates macroeconomic variables, namely the policy interest rate (BI7DRR/BI rate) and inflation from Bank Indonesia, and the Federal Funds Effective Rate (FEDFUNDS). The Table 1 presents the variables used in this study and their respective transformations or calculations.

Monthly volatility (Vol_m) is measured using monthly realized volatility, calculated as the standard deviation of daily returns within each month, following Balaban et al. (2006). Daily returns are computed from the change in the index value between consecutive trading days. Monthly volatility is then obtained by measuring the dispersion of daily returns ($R_{m,t}$)) around their monthly mean ($\bar{R}_m$). The formula used to calculate return volatility is as follows:

$$Vol_m = \sqrt{\frac{\sum_{t=1}^{n}\left(R_{m,t} - \bar{R}_m\right)^2}{n-1}}$$

Meanwhile, the investor sentiment indices are constructed using Principal Component Analysis (PCA), with Google Search Trends (GST) serving as a proxy for investor sentiment. GST provides data on the intensity of keyword searches through the Search Volume Index (SVI), a normalized measure ranging from 0 to 100. A value of 100 indicates the highest search interest for a keyword during the observation period, whereas 0 indicates insufficient or very low search volume for reporting. GST is used as a proxy for investor sentiment based on prior studies showing that GST-based sentiment measures significantly explain stock market dynamics (Mao et al. 2011; Rizkiana et al. 2019; Gao et al. 2022; Szczygielski et al. 2024). Given the limited availability of direct measures of market-wide investor sentiment, GST can capture prevailing market conditions through users' search intensity. Accordingly, economy- and capital-market-related keywords are selected to construct the investor sentiment indices.

Table 1. Variables, sources, and measurement procedures

	Variable	Description	Data Source
Dependent Variable	Return volatility of IHSG (Vol_IHSG))	IHSG return volatility is calculated using the IHSG closing prices, from which returns and subsequently volatility are derived (see the detailed explanation following the table)	IHSG closing price data were obtained from Yahoo Finance
Independent Variable	Turnover ratio (Turnover)	The turnover ratio is calculated by dividing the total value of shares traded by the total market capitalization	Trading value and market capitalization data were obtained from the Indonesia Stock Exchange (IDX)
	Sent_pos Sent_neg	GST data for each keyword were first grouped into positive sentiment (IPO, economic growth, and dividends) and negative sentiment (stock market decline, economic crisis, bankruptcy, and layoffs). Subsequently, Principal Component Analysis (PCA) was applied to construct two composite indices, namely Sent_pos (positive sentiment index) and Sent_neg (negative sentiment index)	Google Search Trend
Interaction terms	Interaksi_pos Interaksi_neg	The interaction terms are constructed by multiplying the investor sentiment indices by the turnover ratio	The variables used in the calculations were obtained from Google Search Trends (GST) and the Indonesia Stock Exchange (IDX)
Macroeconomic variables	Policy rate (BI_rate)	Indonesia's policy interest rate	Bank Indonesia
	Inflasi (Inf)	Percentage Change in the Consumer Price Index (CPI)	Bank Indonesia
	Federal Funds Effective Rate (FED)	U.S. Federal Funds Rate	FRED

Eight keywords were selected to capture investor sentiment in the Indonesian capital market, drawing on prior studies that employ terms such as bull market, bear market, bankruptcy, and crisis as sentiment indicators (Mao et al. 2011; Da et al. 2015; Gao et al. 2015; Brochado, 2020). Additional keywords were adapted from the LM Dictionary to reflect economic and financial contexts in the Indonesian language (Ballinari & Behrendt, 2021), yielding four positive sentiment keywords, namely IPO, economic growth, rising stocks, and dividends, and four negative sentiment keywords, namely falling stocks, economic crisis, bankruptcy, and layoffs. This approach improves the relevance of the sentiment measures to Indonesian investors, although it does not capture the search behavior of foreign investors. For each keyword, SVI values were aligned over the observation period and standardized into z-scores to ensure comparability. Principal Component Analysis (PCA) was then applied separately to the positive and negative keyword groups to extract a principal component that captures the largest share of the common variation across keywords and summarizes the underlying investor sentiment.

PCA generates components with corresponding eigenvalues and loadings, with components retained based on the Kaiser criterion of eigenvalues greater than one. The first principal component, which explains the largest share of variation, is used to construct the sentiment index, with its loadings serving as weights for aggregating individual keyword indices. PCA is performed separately for positive and negative keywords, producing two composite indices, namely positive sentiment and negative sentiment, which are subsequently included as investor sentiment variables in the model. This approach reduces multicollinearity among keywords while providing more representative composite measures than individual keywords. Meanwhile, the turnover ratio is defined as the ratio of traded value to market capitalization, following Levine and Zervos (1996).

The relationship between investor sentiment and liquidity, including the moderating role of liquidity, is examined using the Autoregressive Distributed Lag (ARDL) model combined with an Error Correction Model (ECM). Before estimation, several preliminary tests are conducted, including unit root tests to assess stationarity, optimal lag selection, and diagnostic tests to ensure model adequacy. The Error Correction Model (ECM) and Autoregressive Distributed Lag (ARDL) are closely related econometric approaches for examining dynamic relationships among nonstationary variables (Phillips & Loretan, 1991). ARDL captures short- and long-run effects through lagged variables, while its ECM representation incorporates long-run cointegration and short-run adjustments (Mokhtari, 1992; Pesaran, 2015).

The model builds on prior studies using Google Search Trends as a proxy for investor sentiment (Brochado, 2020; Da et al. 2015; Gao et al. 2015; Mao et al. 2011), while Widhiarti et al. (2018) identify investor sentiment as a determinant of stock market returns and volatility. The turnover ratio is adopted as an objective measure of market liquidity following Sarr and Lybek (2002). The study specifies three models to examine the effects of positive and negative investor sentiment on IHSG return volatility, with the turnover ratio included as a moderating variable across all models. Model 1 focuses on positive sentiment, Model 2 on negative sentiment, and Model 3 jointly examines both sentiment measures and their interaction with the turnover ratio. All models control for the BI Rate, inflation, and the Federal Funds rate to account for macroeconomic influences on Indonesian stock market volatility. The following are the long-run ARDL model equations:

Model 1

$$LnVol_{IHSG_t} = \beta_0 + \sum_{i=1}^{p} \beta_i LnVol_IHSG_{t-i} + \sum_{j=0}^{q_1} \gamma_j Sent_pos_{t-j} + \sum_{k=0}^{q_2} \delta_k Turnover_{t-k} + \sum_{l=0}^{q_3} \theta_l Interaksi_pos_{t-l} + \sum_{m=0}^{q_4} \lambda_m BI_Rate_{t-m} + \sum_{n=0}^{q_5} \mu_n INF_{t-n} + \sum_{o=0}^{q_6} \rho_o FED_{t-o} + \varepsilon_t$$

Model 2

$$LnVol_{IHSG_t} = \beta_0 + \sum_{i=1}^{p} \beta_i LnVol_IHSG_{t-i} + \sum_{j=0}^{q_1} \gamma_j Sent_neg_{t-j} + \sum_{k=0}^{q_2} \delta_k Turnover_{t-k} + \sum_{l=0}^{q_3} \theta_l Interaksi_neg_{t-l} + \sum_{m=0}^{q_4} \lambda_m BI_Rate_{t-m} + \sum_{n=0}^{q_5} \mu_n INF_{t-n} + \sum_{o=0}^{q_6} \rho_o FED_{t-o} + \varepsilon_t$$

Model 3

$$LnVol_{IHSG_t} = \beta_0 + \sum_{i=1}^{p} \beta_i \, LnVol_{IHSG_{t-i}} + \sum_{j=0}^{q_1} \gamma_j \, Sent_pos_{t-j} + \sum_{k=0}^{q_2} \delta_k \, Sent_neg_{t-k} + \sum_{l=0}^{q_3} \theta_l \, Turnover_{t-l} + \sum_{m=0}^{q_4} \lambda_m \, Interaksi_pos_{t-m} + \sum_{n=0}^{q_5} \phi_n \, Interaksi_neg_{t-n} + \sum_{o=0}^{q_6} \mu_o \, BI_Rate_{t-o} + \sum_{r=0}^{q_7} \eta_r \, INF_{t-r} + \sum_{s=0}^{q_8} \rho_s \, FED_{t-s} + \varepsilon_t$$

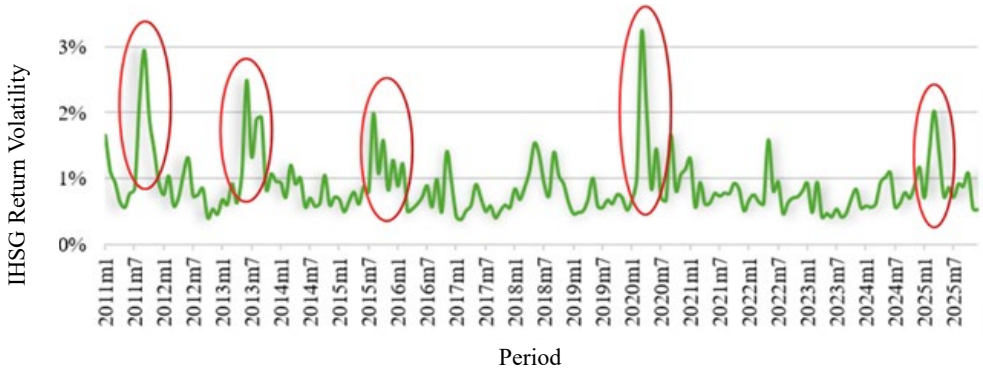
where $LnVol_{IHSGt}$ is IHSG return volatility; $sent_pos_t$ is Google Trends search index representing positive investor sentiment; $sent_neg_t$ is Google Trends search index representing negative investor sentiment; $Turnover_t$ is stock trading activity ratio (turnover ratio), interaksi_pos is interaction term between positive investor sentiment and turnover ratio; interaksi_neg is interaction term between negative investor sentiment and turnover ratio; BI_Rate_t is Bank Indonesia's policy interest rate; INF_t is Indonesia's inflation rate, and FED_t is the Federal Funds Rate, the benchmark interest rate set by the US Federal Reserve.

RESULTS

Indonesia's capital market experienced substantial development over the 2011–2025 study period. The Jakarta Composite Index (IHSG) reflects not only national economic performance but also the interaction between domestic and foreign investor sentiment and macroeconomic conditions in shaping stock return volatility. Major domestic and global events, ranging from economic uncertainty to policy changes, have further influenced IHSG movements, highlighting the evolving dynamics of Indonesia's capital market (Figure 2).



(a) Dynamics of the Jakarta Composite Index/IHSG (Closing Price) (Yahoo Finance, 2026)



(b) IHSG Return Volatility (2011–2025)

Figure 2. IHSG trends and return volatility

In 2011, the IHSG continued to recover from the 2008 global financial crisis, although market optimism remained fragile and foreign investment played a substantial role in Indonesia's economy (Susianto et al. 2012). Market uncertainty intensified following the US sovereign credit rating downgrade in August 2011, triggering capital outflows from emerging markets and heightened volatility (Arezki et al. 2011). Similar vulnerabilities emerged during the 2013 taper tantrum, when the Federal Reserve's announcement of reduced quantitative easing triggered foreign capital withdrawals and sharp declines in Indonesian financial markets. Despite being classified among the Fragile Five, Indonesia restored stability within approximately seven months through coordinated monetary, macroprudential, and fiscal measures (Basri, 2017; Warjiyo, 2014). These developments illustrate how external shocks and investor sentiment can amplify return volatility, particularly when market reactions diverge from underlying fundamentals (Sahay et al. 2014a). In 2015, renewed global uncertainty and US–China trade tensions further intensified capital outflows, contributing to Indonesia's economic growth slowdown from 5.02% in 2014 to 4.71% in 2015 (Al-Fadhat and Nadhir, 2019).

During 2016–2019, Indonesia's capital market gradually strengthened alongside structural reforms and growing domestic retail participation. The reduction in the minimum trading lot to 100 shares in 2014 lowered entry barriers, supporting broader investor participation and reducing reliance on volatile foreign capital. Despite declining capital inflows, Indonesia demonstrated resilience during the 2018 recovery, with no substantial output losses (Indrawati et al. 2020). The COVID-19 pandemic subsequently triggered one of the sharpest market declines in the study period, with the IHSG falling from above 6,000 to 3,937.63 on March 24, 2020. This episode further highlighted the role of investor psychology, sentiment, and expectations in shaping stock prices and return volatility under heightened uncertainty (Naik and Padhi, 2016; Rupande et al. 2019).

Despite the pandemic, Indonesia's capital market expanded as mobility restrictions and digital investment platforms encouraged greater retail participation. The number of investors rose from 3.88 million in 2020 to 7.49 million in 2021 and 10.31 million in 2022 (KSEI, 2020; KSEI, 2021; KSEI, 2022), strengthening the role of domestic investors in market sentiment and liquidity. This trend continued during 2023–2025, with investor numbers increasing from 12.17 million to 20.35 million (KSEI, 2023; KSEI, 2024; KSEI, 2025), reflecting deeper market participation despite persistent global volatility. Retail trading activity is positively associated with stock market liquidity and market quality (Abudy, 2020). Furthermore, market capitalization reached IDR12,336 trillion at the end of 2024, exceeding its 2020–2024 historical average and underscoring the capital market's growing significance in Indonesia's economy.

Building on the descriptive analysis of IHSG movements and return volatility, the following section presents the PCA results used to construct positive and negative investor sentiment indices. PCA reduces the dimensionality of multiple sentiment proxies into composite measures, enabling a systematic examination of sentiment dynamics in Indonesia's capital market.

The PCA results for positive sentiment keywords indicate that the first principal component (Comp1) has an eigenvalue of 2,399 and explains 59.98% of the total variance, exceeding the Kaiser criterion of 1. Accordingly, Comp1 is retained to construct the positive sentiment index. All four keywords have positive loadings on the first principal component, with stock price increases (0.604) contributing the most, followed by IPOs (0.560), dividends (0.536), and economic growth (0,185). For negative sentiment, Comp1 has an eigenvalue of 2.002 and explains 50.05% of the total variance, also satisfying the retention criterion. The first principal component exhibits positive loadings for all four keywords, namely stock price decreases (0.5183), economic crisis (0.4398), bankruptcy (0.4687), and layoffs (0.5642). Thus, PCA reduces the Google Trends keywords into two composite indices representing positive and negative investor sentiment. These indices serve as proxies for investor sentiment in the subsequent analysis of IHSG return volatility.

Before estimating the ARDL models, unit root tests, optimal lag selection, and bounds tests for cointegration were conducted. The stationarity results indicate that all variables are stationary at first differences (Table 2). The Akaike Information Criterion (AIC) was used to select the optimal lag structure, as it balances model fit and complexity, particularly for relatively small samples. The model with the lowest AIC was selected for subsequent analysis (Table 3). Bounds test results confirm long-run cointegration between IHSG return

volatility and the explanatory variables across all three models (Table 3). Post-estimation diagnostic tests further indicate no evidence of serial correlation or heteroskedasticity, while the CUSUM test confirms parameter stability, supporting the adequacy of the estimated models.

After satisfying the preceding diagnostic tests, the ARDL–ECM model is estimated to examine both the long-run and short-run relationships between IHSG return volatility and the explanatory variables. The ECM component further captures the speed at which the model adjusts toward long-run equilibrium following a deviation from the equilibrium path.

Table 4 presents the estimation results for the three models, all of which exhibit negative and statistically significant ECT coefficients at the 1% level (p = 0.000). The ECT coefficients are −0.526, −0.534, and −0.555 for Models 1, 2, and 3, respectively, confirming the presence of a stable long-run adjustment mechanism. These estimates indicate that approximately 52.6%, 53.4%, and 55.5% of short-run deviations from long-run equilibrium are corrected within the following month in Models 1, 2, and 3, respectively.

This study examines the relationships between investor sentiment, capital market liquidity, and IHSG return volatility using three model specifications. Model 1 includes positive sentiment, Model 2 includes negative sentiment, and Model 3 incorporates both simultaneously as a robustness check. All models include the turnover ratio as a proxy for market liquidity, sentiment liquidity interaction terms, and macroeconomic controls consisting of the policy rate, inflation, and the Federal Funds Rate. Model 3 confirms the robustness of the negative sentiment effect, which remains positive and significant after controlling for positive sentiment, suggesting that negative sentiment plays a more prominent role in explaining IHSG return volatility. In contrast, positive sentiment, which is significant in Model 1, becomes insignificant in Model 3, indicating that its incremental contribution diminishes when negative sentiment is considered simultaneously.

Table 2. Unit root test results

Variables	Level (I(0))	First difference (I(1))
	t-Statistic	t-Statistic
LnVol_IHSG	-8.039***	-18.075***
Sent_pos	-0.626	-15.986***
Sent_neg	-4.000***	-15.980***
Turnover	-7.282***	-19.567***
Interaksi_pos	-1.610	-16.087***
Interaksi_neg	-4.189***	-16.843***
BI_Rate	-0.998	-8.2120***
INF	-2.185	-10.602***
FED	-0.134	-5.8740***

Table 3. Optimal lag length selection

Variables	Model 1	Model 2	Model 3
LnVol_IHSG	1	2	2
Sent_pos	0		0
Sent_neg		0	0
Turnover	1	1	0
Interaksi_pos	0		1
Interaksi_neg		0	0
BI_Rate	1	1	1
INF	0	0	0
FED	2	2	2

Table 4. Bounds test for cointegration results

Model	Test Statistic	Value	Sig	I(0)	I(1)
Model 1	F-statistic	10.279	10%	2.154	3.284
	K	6	5%	2.497	3.708
			1%	3.236	4.602
Model 2	F-statistic	9.008	10%	2.150	3.285
	K	6	5%	2.493	3.709
			1%	3.232	4.604
Model 3	F-statistic	9.158	10%	1.971	3.122
	K	8	5%	2.260	3.491
			1%	2.883	4.266

Table 5. ARDL–ECM estimation results for IHSG return volatility

	Variables	Model 1	Model 2	Model 3
ARDL	L1.LnVol_IHSG	0.474***	0.432***	0.399***
	L2.LnVol_IHSG		0.035	0.045
	Sent_pos	0.002**		0.001
	Sent_neg		0.003***	0.002*
	Turnover	0.229***	0.218***	0.213***
	L1.Turnover	-0.063	-0.060	
	Interaksi_pos	-0.069***		0.022
	L1.Interaksi_pos			-0.015
	Interaksi_neg		-0.100***	-0.075
	BI_Rate	0.005***	0.006***	0.005***
	L1.BI_Rate	-0.004***	-0.004***	-0.004***
	INF	-0.001	-0.001	-0.001
	FED	-0.011***	-0.012***	-0.011***
	L1.FED	0.017***	0.019***	0.018***
	L2.FED	-0.006**	-0.008***	-0.007***
Short-run	D(Sent_pos)	0.002**		0.001
	D(Sent_neg)		0.003***	0.003*
	D(turnover)	0.229***	0.218***	0.214***
	D(Interaksi_pos)	-0.069***		-0.022
	D(Interaksi_neg)		-0.100***	-0.075
	D(BI_Rate)	0.005***	0.006***	0.005***
	D(INF)	-0.001	-0.001	-0.001
	D(FED)	-0.011***	-0.012***	-0.011***
	D(FED(-1))	0.006**	0.008***	0.007***
	ECT(-1)	-0.526***	-0.534***	-0.555***
	Adjusted R-squared	0.422	0.433	0.431
Long-run	Sent_pos	0.004**		0.001
	Sent_neg		0.006***	0.005*
	Turnover	0.317***	0.296***	0.385***
	Interaksi_pos	-0.132***		-0.067
	Interaksi_neg		-0.188***	-0.135
	BI_Rate	0.001	0.001	0.001
	INF	-0.001	-0.001	-0.001
	FED	-0.001	-0.001**	-0.001

The turnover ratio remains positive and significant across the model specifications, confirming the persistent role of market liquidity in explaining IHSG return volatility in the long-run. However, the interaction terms between sentiment and turnover ratio become insignificant in Model 3, suggesting that the moderating effect of liquidity depends on the specification and measurement of investor sentiment. This finding highlights the need for further research using alternative sentiment proxies and longer observation periods. Meanwhile, the macroeconomic controls are insignificant in Model 3, indicating that their effects on IHSG volatility are relatively transitory. Market liquidity, proxied by the turnover ratio, moderates the effect of investor sentiment on IHSG return volatility. The long-run estimates in Table 4 show that the interactions between liquidity and both positive and negative sentiment are negative and statistically significant at the 1% level, with coefficients of −0.132 and −0.188 in Models 1 and 2, respectively. However, the marginal effects presented in Table 5 reveal important differences across liquidity levels. For an interaction model between investor sentiment and market liquidity, the marginal effect measures how the effect of sentiment on volatility changes at different levels of liquidity. At high liquidity levels (the 95th and 99th percentiles), positive sentiment has a significantly weaker effect on IHSG return volatility. Conversely, at lower liquidity levels (the 1st–50th percentiles), liquidity significantly amplifies the effect of negative sentiment on volatility.

One possible explanation, consistent with behavioral finance theory, is that investor sentiment may trigger overreaction, herding behavior, and other behavioral biases, potentially intensifying trading pressure and contributing to greater market volatility (Guo et al. 2025). In highly liquid markets, greater market depth enables large buying or selling pressures to be absorbed with smaller price impacts, thereby limiting volatility (Bouchaud et al. 2008; Enow et al. 2022). This mechanism is particularly important during periods of negative sentiment, when coordinated selling can exert substantial downward pressure on prices. Low liquidity limits the market's ability to absorb such pressure, resulting in sharper price movements and higher volatility, whereas stronger liquidity helps mitigate these effects (Chiu et al. 2018; López-Cabarcos et al. 2020). Overall, the findings suggest that market liquidity may moderate the relationship between investor sentiment and volatility, although this effect is sensitive to model specification and is not significant when both sentiment measures are included simultaneously.

Table 5. Estimated marginal effects

Model 1: Positive Sentiment–Liquidity Interaction			
Persentile	Turnover ratio level	Marginal effect	Prob.
1%	0.017	0.002	0.055
5%	0.019	0.001	0.081
10%	0.020	0.001	0.101
25%	0.022	0.001	0.164
50%	0.026	0.001	0.502
75%	0.030	-0.001	0.742
90%	0.036	-0.001	0.086
95%	0.039	-0.001	0.032
99%	0.061	-0.004	0.005
Model 2: Negative Sentiment–Liquidity Interaction			
Persentile	Turnover ratio level	Marginal effect	Prob.
1%	0.017	0.003	0.001
5%	0.019	0.002	0.001
10%	0.020	0.002	0.001
25%	0.022	0.002	0.002
50%	0.026	0.001	0.017
75%	0.030	0.001	0.428
90%	0.036	-0.001	0.233
95%	0.039	-0.001	0.092
99%	0.061	-0.005	0.008

IHSG return volatility exhibits significant persistence across all three models, with lagged volatility coefficients of 0.474, 0.432, and 0.399, indicating that approximately 40% to 47% of previous period volatility carries over to the current period. Positive investor sentiment has a positive and significant effect on volatility in Model 1, both in the short and long-run, but becomes insignificant when negative sentiment is included in Model 3. In contrast, negative sentiment consistently exhibits a positive and significant effect in Models 2 and 3, with stronger long-run effects. However, these estimates should be interpreted conditionally, as the effects of sentiment depend on the level of liquidity through the interaction term. This asymmetric response supports the behavioral finance perspective and the presence of negativity bias, whereby investors tend to react more strongly to adverse information than to favorable information (Kahneman & Tversky, 1979; Baumeister et al. 2001). The findings are consistent with previous evidence linking investor sentiment to stock market volatility, including in Indonesia and other ASEAN markets (Widhiarti et al. 2018; Sukmadilaga et al. 2023; Qatrunnada, 2024).

The turnover ratio has a positive and significant effect on IHSG return volatility across all three models in both the short and long-run, with coefficients ranging from 0.213 to 0.229 in the short-run and 0.296 to 0.385 in the long-run. However, these coefficients reflect conditional effects, as the relationship between the turnover ratio and IHSG return volatility varies with the level of investor sentiment. This indicates that greater trading activity is associated with higher volatility, potentially because increased transactions accelerate price discovery and amplify short-term price adjustments to new information. The absence of a significant effect at the second lag suggests that this impact is primarily concentrated during the initial information absorption process. These findings are consistent with previous studies associating trading activity and turnover with higher stock return volatility (Urooj et al. 2019; Wijaya et al. 2025).

The macroeconomic controls exhibit predominantly short-lived effects. The policy rate has a positive and significant contemporaneous effect on volatility but becomes insignificant in the long-run, while its first lag has a negative effect, suggesting an initial market response followed by adjustment as monetary policy information is absorbed. Inflation is insignificant across all specifications and periods, indicating limited direct effects on IHSG volatility. The Fed Funds Rate shows a negative and significant short-run effect across all models, but its long-run effect is significant only in Model 2, suggesting that global monetary policy shocks may have more persistent implications when domestic investor sentiment is negative. Overall, these findings indicate that IHSG volatility is more persistently associated with investor sentiment and market trading activity, whereas the effects of domestic macroeconomic conditions are largely transitory and global monetary shocks operate through a more dynamic adjustment process.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study finds that investor sentiment and market liquidity play important roles in explaining IHSG return volatility. Negative sentiment exhibits a positive and significant effect across model specifications, whereas positive sentiment becomes insignificant when both sentiment measures are included simultaneously, highlighting the asymmetric influence of investor sentiment. Market liquidity plays a dual role in shaping volatility. Higher turnover is positively associated with return volatility, suggesting that intensive trading activity may amplify short-term price adjustments. However, marginal effect analysis indicates that high liquidity attenuates the impact of positive sentiment, while lower liquidity amplifies the effect of negative sentiment. Importantly, these moderating effects are observed when positive and negative sentiment, along with their respective interaction terms with turnover ratio, are estimated in separate models. When both sentiment measures and interaction terms are included simultaneously, neither moderating effect remains statistically significant. Thus, the moderating role of liquidity appears to be sensitive to model specification and should be interpreted with caution. Meanwhile, macroeconomic variables primarily exhibit short-run effects, with limited evidence of persistent long-run relationships. Overall, the results highlight the importance of considering sentiment asymmetry, trading activity, and liquidity conditions jointly to understand stock market volatility in an emerging market such as Indonesia.

Recommendations

The findings offer several implications for investors, regulators, and future research. Investors should incorporate sentiment indicators and liquidity conditions into risk management strategies, particularly during periods of negative sentiment and limited market liquidity, when volatility may intensify. The consistent positive and significant effect of the turnover ratio across all model specifications further highlights the importance of monitoring trading activity as an indicator of market volatility. Regulators and market authorities should therefore strengthen market surveillance, particularly during periods of unusually high trading activity and heightened uncertainty, while improving investor communication and promoting market resilience. Given the persistent nature of volatility, monitoring trading activity and sentiment dynamics may also support early-warning mechanisms for emerging market stress.

This study has a limitation in the relatively small number of Google Search Trends (GST) keywords used to construct the sentiment indices, which may not fully capture the multidimensional nature of investor sentiment. Future research could incorporate a broader range of keywords to improve the comprehensiveness and robustness of sentiment measurement. Incorporating structural breaks, regime-switching dynamics, and major financial events may further clarify how sentiment–liquidity interactions evolve across market conditions. Comparative studies across ASEAN markets could also establish whether the observed asymmetry between positive and negative sentiment is specific to Indonesia or reflects a broader characteristic of emerging capital markets.

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