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Does AI Sentiment Affect Stock Returns? Evidence from Indonesia's Banking Sector

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Abstract

This study investigates the heterogeneous effects of AI-related investor sentiment on the stock returns of Indonesian banks. Using a correlation-weighted AI Sentiment Index (AI-SVI) derived from Google Trends, panel regressions reveal that only fintech-driven banks show significant responsiveness to AI sentiment, while conventional, independent digital, and conglomerate-backed banks do not. These findings are supported by a supplementary investor perception survey, which confirms that market participants associate visible and strategic AI adoption primarily with fintech institutions. The results suggest that AI sentiment can act as a behavioral signal of valuation in emerging financial markets, but its effectiveness depends on how innovation is perceived and communicated. Policymakers and investors should be cautious in interpreting sentiment-driven movements, especially in sectors with uneven technological maturity.

Keywords: AI Sentiment; Google Trends; Bank Stock Returns; Fintech; Emerging Markets; Behavioral Finance.

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1. Introduction

Indonesia, as one of Southeast Asia's most dynamic digital economies, is experiencing a rapid transformation in its banking sector driven by artificial intelligence (AI) and digital innovation. From enhancing credit risk evaluation to automating customer interactions, AI has become integral to modern financial services. According to Citi GPS, 93% of global financial institutions believe that AI will increase profitability, with the banking sector projected to gain USD 170 billion by 2028 (Ghose et al., 2024). As Indonesian banks increasingly adopt AI technologies, it is important to understand how these innovations affect investor behavior, particularly in the capital market. Beyond operational advantages, AI influences investor sentiment, which can drive stock price movements. The growing frequency of AI-related searches on platforms like Google Trends reflects rising market attention, which behavioral finance literature identifies as a key driver of asset mispricing (Bonaparte, 2024; Da et al., 2015). In particular, Bonaparte (2024) demonstrated that spikes in public interest in AI can predict stock returns in technology-focused companies. This supports the broader view that sentiment-based indicators can provide insight into investor psychology, especially in markets with information frictions (Baker & Wurgler, 2006; Stambaugh et al., 2012). However, most empirical studies on AI sentiment and stock returns have focused on developed markets, while the literature on emerging economies remains sparse. In the context of Indonesia, Hamadou et al. (2024) examined AI adoption within Bank Syariah Indonesia and highlighted both the opportunities and constraints faced by Islamic banks in integrating AI. Although their study provides critical insights into organizational readiness and ethical considerations, it does not address the market-level impact of AI sentiment on financial assets. This gap is important, especially given Indonesia's diverse banking landscape that includes traditional, digital, and fintech-driven institutions. This study aims to fill that gap by constructing a real-time, correlation-weighted AI Sentiment Index (AI-SVI) using Google Trends data. Following Bonaparte (2024), five AI-related keywords are tracked to measure investor attention, which is then used to explain stock return variations. The index weights each keyword based on its historical correlation with banking stock returns in Indonesia, enhancing its relevance as a proxy for sentiment-driven price movements**.** The analysis applies Ordinary Least Squares (OLS) regression models across four categories of IDX-listed banks: (1) conventional banks adopting digital strategies, (2)

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digital banks under financial conglomerates, (3) independent digital banks, and (4) fintech-driven banks. Control variables include the Jakarta Composite Index (IHSG) and return volatility. This research offers four key contributions. First, it introduces a localized, real-time AI Sentiment Index (AI-SVI) based on Google Trends data, tailored to the Indonesian financial context, which serves as a novel proxy for investor attention toward AI. Second, it provides evidence of heterogeneous effects of AI sentiment across different banking models—conventional, conglomerate-backed, independent digital, and fintech-driven—highlighting how institutional structures and digital maturity influence market response. Third, to complement the empirical analysis, this study incorporates an investor perception survey to capture how individual investors evaluate the role of AI in banking. The survey offers behavioral insights that validate and enrich the regression findings, particularly in understanding how sentiment translates into investment decisions. Fourth, the study suggests that AI sentiment may act as a behavioral indicator of valuation pressures, helping market participants distinguish between price movements driven by fundamentals and those driven by investor enthusiasm. These contributions extend the literature on sentiment-based asset pricing and provide practical tools for evaluating digital transformation in emerging markets.

The remainder of this paper is organized as follows**.** Section 2 reviews the relevant literature on investor sentiment, AI adoption in financial services, and the use of Google Trends as a proxy for behavioral signals in capital markets. Section 3 outlines the research methodology, including the construction of the AI Sentiment Index (AI-SVI), data sources, sample classification, and the regression model. Section 4 presents the empirical results, supported by robustness checks and investor survey insights. Section 5 concludes with a summary of findings, theoretical and practical implications, study limitations, and suggestions for future research.

2. Literature Review

2.1. Evolution of Sentiment-Based Asset Pricing

How assets are priced has long been one of the core questions in finance. The Capital Asset Pricing Model (CAPM), independently developed by Sharpe (1964), Lintner (1965), and Mossin (1966), provided a foundational framework by proposing that expected returns are determined solely by exposure to systematic market risk, proxied by beta. Investors are compensated only for bearing non-diversifiable risk, while firm-specific risks are presumed irrelevant under portfolio diversification. However, as capital markets evolved and information became more widely available, researchers began to identify persistent patterns that CAPM could not explain. Fama & French (1992) introduced a three-factor asset pricing model that incorporated firm size and book-to-market ratios as additional explanatory variables beyond market risk. Their findings highlighted persistent return anomalies—such as the size effect and value premium—that could not be explained by the Capital Asset Pricing Model (CAPM), thereby challenging the sufficiency of single-factor models in capturing asset price behavior. At the same time, the Efficient Market Hypothesis (EMH), formalized by Fama (1970), argued that financial markets are informationally efficient, meaning that asset prices fully and rapidly reflect all available information. The semi-strong form of EMH, in particular, holds that prices immediately adjust to public news, leaving no room for predictable excess returns. However, frequent episodes of bubbles, crashes, and momentum effects have repeatedly challenged this assumption. These market behaviors are too systematic and widespread to be attributed to chance alone, prompting the rise of behavioral finance as an alternative perspective. Behavioral finance introduces psychological and cognitive factors into asset pricing, emphasizing that investors are not always rational and are often influenced by heuristics and biases. Scholars such as Baker & Wurgler (2006) and Stambaugh et al. (2012) have emphasized the role of investor sentiment—expectations and emotions not grounded in fundamentals—as a key driver of stock price deviations. Sentiment effects are often magnified in assets that are difficult to value or costly to arbitrage, including those in high-growth or technology sectors. This perspective marks a significant shift in the asset pricing paradigm, moving beyond risk-based explanations to incorporate attention-based and behavioral drivers.

2.2. Behavioral Finance and Investor Attention

While traditional asset pricing theories assume rational investors and fully efficient markets, behavioral finance offers an alternative view by highlighting the impact of cognitive limitations and attention constraints. Investors often focus on salient, emotionally charged, or trending information rather than processing all available data objectively. This limited attention becomes particularly relevant in environments with rapid innovation and information overload, such as the technology and artificial intelligence (AI) sectors. Provide empirical support for this mechanism by showing that spikes in internet search activity are strongly correlated with changes in stock returns and volatility. These search patterns serve as a proxy for investor attention, which in turn reflects collective sentiment. More recently, Bonaparte (2024) demonstrated that rising attention to AI—measured through search volumes of specific AI-related terms—can drive sentiment-fuelled price movements in technology stocks. His findings suggest that even in fundamentally strong sectors, investor enthusiasm can lead to short-term overpricing and subsequent corrections. These insights form the theoretical foundation of the current study. By capturing investor attention through AI-related search trends, we aim to quantify behavioral influences on asset pricing in Indonesia's banking sector. Given the sector's diverse levels of digitalization, sentiment toward AI is unlikely to affect all banks uniformly. As such, a sentiment-based framework offers a useful complement to traditional asset pricing models, particularly in emerging markets where information frictions and behavioral bia**ses** are more pronounced.

2.3. Empirical Evidence on Sentiment and Stock Return

Empirical studies increasingly support the idea that investor sentiment can significantly influence asset prices beyond what fundamentals alone can justify. Preis et al. (2013) found that surges in internet searches for financial terms tend to precede increased market volatility, indicating that public attention is a leading indicator of market behavior. Building on this foundation, Da et al. (2015) introduced the Search Volume Index (SVI), showing that elevated search activity for firm-specific terms is associated with both higher short-term volatility and lower subsequent returns. This pattern implies that increased investor attention often reflects speculative enthusiasm rather than informed analysis. Expanding this approach to the AI domain, Bonaparte (2024) constructed a sentiment index based on Google Trends data for AI-related keywords such as "machine learning" and "neural networks." His study found a significant correlation between AI sentiment and stock returns in U.S. technology firms. Importantly, the impact of AI sentiment was not universally positive periods of intense attention sometimes led to overvaluation and eventual corrections, highlighting the dual role of sentiment as both a driver of optimism and a source of market risk. Despite these developments, there remains a noticeable gap in the literature regarding sentiment and stock returns in emerging markets. While the use of search-based sentiment indices has become more common in developed economies, few studies have focused on constructing AI-specific indices tailored to the institutional and behavioral characteristics of emerging financial systems. This study seeks to fill that gap by developing an AI Sentiment Index designed for the Indonesian banking sector.

2.4. AI Sentiment Index

This study constructs an AI Sentiment Index (AI-SVI) based on Google Trends data to capture changes in public attention toward artificial intelligence. Following the approach of Preis et al. (2013) who demonstrated that increases in search volume for financial terms can predict market movements and volatility, this study adopts Google Trends as a real-time proxy for investor attention. In line with Bonaparte (2024), the AI-SVI aggregates daily search volumes for selected AI-related keywords, including "Artificial Intelligence," "Machine Learning," "Deep Learning," "Neural Networks," and "Generative AI." Each keyword's search interest is collected on a daily basis, and the combined index reflects the overall level of public focus on AI-related developments. The use of English-language keywords to construct a sentiment index based on Google Trends is widely accepted, including in studies conducted in emerging markets. Prior research confirms that English terms effectively capture investor attention across non-English-speaking countries, enabling consistency in cross-country comparisons and reflecting common usage in financial contexts (Ayala et al., 2024; Padungsaksawasdi et al., 2019; Swamy & Dharani, 2019). Google Trends thus offers a dynamic and accessible tool to monitor sentiment shifts that may not yet be reflected in fundamentals or news media. In this study, the AI-SVI serves as the key independent variable in a series of regression models analyzing whether attention to AI influences the stock returns of Indonesian banks. By comparing effects across different types of banks—conventional, digital, conglomerate-backed, and fintech-driven—the analysis sheds light on how technological narratives interact with institutional structures in shaping market behavior

3. Methods

3.1 Research Design

This study adopts a quantitative explanatory research design to investigate whether increasing public attention toward artificial intelligence (AI)—as measured by Google Trends search activity—affects stock returns of banking companies in Indonesia. The AI Sentiment Index (AI-SVI) is constructed using five keywords (*Artificial Intelligence*, *Machine Learning*, *Deep Learning*, *Neural Network*, and *Generative AI*), each weighted based on its historical correlation with stock returns. This approach follows the method proposed by Lui et al. (2022), which emphasizes relevance-weighted sentiment construction for improved accuracy in reflecting investor attention. To analyze the relationship between AI sentiment and stock performance, the study employs panel data regression across four categories of banks: conventional banks, digital banks under financial conglomerates, independent digital banks, and fintech-driven banks. Panel regression models are suitable for high-frequency sentiment studies, as demonstrated by Preis et al. (2013), who show that daily search-based attention can effectively capture short-term shifts in market behavior. This framework enables cross-sectional and temporal comparisons, providing a robust empirical basis for testing whether AI-related attention acts as a meaningful valuation signal in the Indonesian banking sector.

3.2 Variable and Data Description

This study utilizes daily data from January 2019 to December 2024 to examine whether public attention toward artificial intelligence (AI) influences stock returns in Indonesia's banking sector. The variables used include stock return, market return, stock volatility, and a custom-built AI Sentiment Index (AI-SVI). All data are aligned at daily frequency and processed using Microsoft Excel and Stata.

3.2.1 Sample Selection

The sample consists of eight financial institutions listed on the Indonesia Stock Exchange (IDX), classified into four categories based on digital strategy and ownership structure:

1. Conventional banks adopting digital strategies: BCA, BRI, Mandiri
2. Digital banks under financial conglomerates: Bank Raya, Allo Bank
3. Independent digital banks: Bank Jago, Krom Bank
4. Fintech-driven banks: Bank Amar, Bank Neo Commerce

3.2.2 Stock Return

Stock returns (RET) are calculated using the log return formula:

$$r_t = \ln(Pt / Pt{-}1) \tag{1}$$

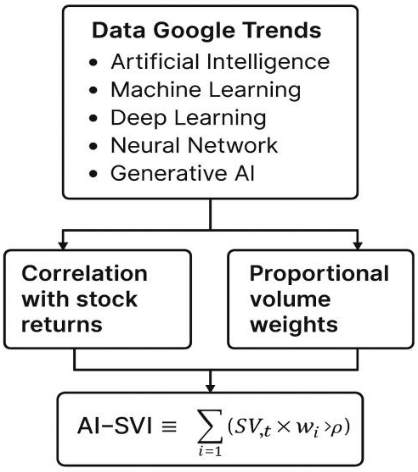
where r_t is the return on day t, Pt and $Pt - 1$ is are the closing stock prices at time t and $t - 1$, respectively. The use of log returns is standard in financial literature due to its additive properties and statistical tractability (Campbell & Shiller, 1988; Fama & French, 1988).

3.2.3 Market Return and Volatility

The Jakarta Composite Index (IHSG) is used to compute daily market return (MKT), applying the same log return formula as above. This variable controls for macroeconomic factors affecting overall market movement. Stock return volatility (VOL) is included as a control variable to capture stock-specific risk. It is calculated as the 60-day rolling standard deviation of daily log returns, using Excel's STDEV.S function. This rolling window approach balances responsiveness to recent price fluctuations with estimation stability, and aligns with common practices in empirical asset pricing literature.

3.2.4 AI Sentiment Index (AI-SVI)

The AI Sentiment Index (AI-SVI) is developed using normalized Google Trends data to quantify public attention toward AI technologies. Based on Preis et al. (2013) and Bonaparte (2024), five key AI-related search terms are selected. Each keyword's daily search volume (scaled 0–100) serves as a proxy for its individual sentiment signal. The index construction involves two steps. First, Pearson correlation coefficients between each keyword's search volume and stock returns are computed over the sample period. These correlations are then normalized to form keyword weights. Second, the daily AI-SVI is calculated as a weighted average of the search volumes, incorporating both relevance (correlation) and intensity (volume). This method captures both the magnitude and market relevance of AI-related attention, resulting in a sentiment index that reflects dynamic public interest with financial significance. The AI-SVI serves as the main independent variable in the return regressions.



Source: Author's illustration using Google Trends data processed in Stata (2025). Note: Constructed using Google Trends data, the AI-SVI combines keyword relevance (correlation with stock returns) and intensity (volume) into a weighted sentiment index.

Figure 1. AI-SVI Construction Framework

3.3 Model Specification

To examine the relationship between AI-related investor sentiment and stock returns, this study employs a linear regression model with the following functional form:

$$Return_{i,t} = \alpha + \beta_1 IndeksAI_t + \beta_2 IHSG_t + \beta_3 Volatility_{i,t} + \varepsilon \tag{2}$$

Where:

- $Return_{i,t}$= the log return of company i's stock at time t
- $IndeksAI_t$ = the Google Trends score for AI-related keywords at time t
- $IHSG_t$ = Jakarta Composite Index (IHSG) as a control variable at time t
- $Volatility_{i,t}$ = volatility of company i's stock returns
- $\epsilon_{i,t}$ = error term

Each regression is estimated using Ordinary Least Squares (OLS) with robust standard errors to correct for potential heteroscedasticity. Given the variation in digital maturity and investor expectations across banking categories, the model is applied separately to each group of firms—allowing the analysis to capture heterogeneous effects of AI sentiment on stock returns. The estimation results aim to identify whether shifts in AI-related public attention are priced differently across traditional banks, digital subsidiaries, independent digital banks, and fintech-driven institutions. This disaggregated approach aligns with the study's objective of exploring how investor sentiment interacts with innovation-based narratives in emerging financial markets.

3.4 Estimation Strategy (by Bank Category)

To capture potential heterogeneity in how investor sentiment toward AI affects financial institutions, the regression model is estimated separately for each bank category as defined in Section 3.2.1. This disaggregated estimation strategy enables the analysis to assess whether AI sentiment has stronger effects on returns for certain types of banks, depending on their business model, digital maturity, and market positioning. For each category, daily stock returns are computed as equal-weighted averages across constituent firms. This allows for group-level panel regressions, isolating the effects of AI-SVI within relatively homogeneous clusters. The approach is particularly relevant in the Indonesian context, where digital transformation progresses unevenly and investor perceptions may vary widely across firm types—from traditional institutions to innovation-driven digital banks.

3.5 Robustness Checks

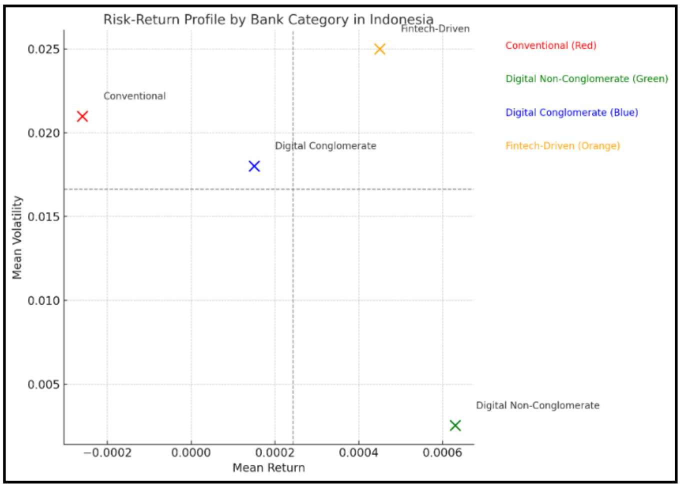
Robustness analyses are implemented to ensure the consistency and validity of the estimation results. The primary strategy involves estimating the model separately for each bank category, allowing the study to identify whether AI sentiment has a differentiated impact depending on institutional type, digital maturity, and investor perception. In addition, all regression models are estimated using robust standard errors to correct for potential heteroskedasticity, enhancing the reliability of inference even when classical OLS assumptions are violated. The robustness of the AI-SVI coefficient is further evaluated by comparing its sign and significance across categories. Consistent patterns across subsamples reinforce the strength of the observed relationship between AI sentiment and stock returns. Lastly, the role of control variables—market return (IHSG) and stock volatility—is assessed within each group. This step confirms that the estimated effect of AI-SVI is not merely capturing broader market trends or firm-specific risks. Together, these robustness checks strengthen the empirical contribution of the study and support the interpretation of AI-related sentiment as a relevant explanatory factor in banking sector return dynamics.

4. Result and Discussions

This section presents the empirical analysis to assess how AI-related investor sentiment affects stock returns across different categories of banks. The discussion begins with a descriptive overview of the key variables to establish the empirical context before proceeding to the main regression results.

4.1. Summary statistics

To provide an intuitive understanding of the dataset, this section presents a descriptive overview of the stock return and volatility characteristics across the four bank categories. Instead of displaying raw descriptive statistics in the main text, we summarize key insights through a risk-return scatter plot (Figure 2) and a simplified classification table (Table 1). The full statistical summary—including mean, standard deviation, minimum, and maximum values (Appendix A).



Source: Authors' analysis from secondary data. Note: The scatter plot shows average daily return (x-axis) and volatility (y-axis) across four bank categories. Quadrants illustrate relative risk-return positions, with colors indicating each category as labeled

Figure 2. Risk-Return Profile by Bank Category in Indonesia

Following the scatter plot visualization in Figure 2, Table 1 presents a concise summary of the return-risk characteristics across the four bank categories. The table provides a qualitative classification based on average daily return and volatility, offering a comparative perspective on each category's position within the broader risk-return spectrum. This classification enhances interpretability and supports the subsequent regression analysis by framing the strategic profiles of each bank type.

Overall, the descriptive findings indicate that the relationship between risk and return is not necessarily linear. Bank categories with higher volatility do not always yield better returns, while price stability does not inherently limit return potential. These insights provide a valuable foundation for the next section, which investigates whether investor sentiment toward AI plays a significant role in explaining return variations across bank types through regression analysis.

Table 1. Summary of Risk-Return Characteristics by Bank Category.

Bank Category	Return	Volatility	Risk-Return Profile
Conventional	Low	High	High Risk – Low Return
Digital non-conglomerate	High	Low	Low Risk – High Return
Digital Conglomerate	Moderate	Moderate-high	Balanced – Medium Risk/Return
Fintech-Driven	High	Very High	High Risk – High Return

Source: Authors' analysis from secondary data

4.2. Regression Analysis

This section presents the results of panel regression estimations conducted to examine the impact of AI-related investor sentiment—proxied by the AI Search Volume Index (AI_SVI)—on stock returns across four bank categories: conventional, digital non-conglomerate, digital conglomerate, and fintech-driven. The models also include IHSG (Jakarta Composite Index) and stock volatility as control variables to account for overall market influence and firm-specific risk. All estimations apply a robust standard error approach to address potential heteroskedasticity commonly observed in daily return data. Table 2 reports the coefficient estimates, p-values, significance levels, and R-squared values for each regression model. The results show that AI_SVI is statistically significant only for fintech-driven banks, with a positive relationship at the 10% significance level. This suggests that public interest in AI, as captured by search behavior, is positively associated with fintech stock returns, possibly due to their explicit reliance on AI narratives in market communication. In contrast, AI_SVI is not statistically significant for conventional, digital non-conglomerate, and digital conglomerate banks.

Table 2. Regression Results

Bank Category	Variable	Coefficient	P-Value	Significance	R2
Conventional	AI-SVI	0,00149	0,371	Not significant	0,1846
	IHSG	1,38186	0,000	***	
	Volatility	-0,13042	0,247	Not significant	
Digital non-conglomerate	AI-SVI	0,00866	0,375	Not significant	0,0393
	IHSG	0,98197	0,000	***	
	Volatility	-0,03161	0,265	Not significant	
Digital Conglomerate	AI-SVI	0,00405	0,302	Not significant	0,0393
	IHSG	1,01086	0,000	***	
	Volatility	0,02803	0,711	Not significant	
Fintech	AI-SVI	0,00685	0,082	*	0,0333
	IHSG	0,99072	0,000	***	
	Volatility	0,08977	0,173	Not significant	

Source: Author's calculation using Stata. Note: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level

Meanwhile, the IHSG control variable is consistently positive and highly significant ($p < 0.001$) across all categories, underscoring the dominant role of market-wide systematic risk in explaining daily stock returns—consistent with the Capital Asset Pricing Model (CAPM). CAPM posits that expected asset returns are primarily determined by exposure to systematic market risk, rather than firm-specific volatility. This interpretation is supported by the fact that volatility was not a significant factor in any of the regression models ($p > 0.10$), indicating that daily price fluctuations—representing idiosyncratic risk—play a limited role in short-term return formation. Although R-squared values are relatively low, this is expected given the use of high-frequency daily data, which inherently contains a large amount of noise and unobserved factors. As highlighted by Da et al. (2011), Google Trends-based sentiment indices typically explain only a small fraction of return variability but remain useful for identifying statistically and economically relevant patterns. Bonaparte (2024) further argues that AI_SVI has limited short-term predictive power, yet serves as an early diagnostic tool for understanding investor perceptions of technological developments. Finally, the results align with the semi-strong form of the Efficient Market Hypothesis (EMH), which asserts that stock prices incorporate all publicly available information, including technological developments like AI. However, the evidence suggests that only fintech-driven banks effectively translate AI-related sentiment into stock performance. Other categories may lack sufficient market signaling to do so. This will be further examined in Section 4.5 through an investor survey aimed at verifying whether public sentiment toward AI aligns with actual investor expectations in the banking sector.

4.3. Statistical Tests

4.3.1. Multicollinearity Test

To ensure the absence of high correlation among independent variables, we conducted a multicollinearity test using the Variance Inflation Factor (VIF). All variables across the four bank categories exhibit VIF values of 1.00, far below the threshold of 10, indicating no multicollinearity and confirming the stability of the regression estimates

Table 3. Variance Inflation Factor (VIF) Results

Bank Category	Variable	VIF	1/VIF
Conventional	AI-SVI	1,00	0,9967
	IHSG	1,00	0,9967
	Volatility	1,00	0,9998
Digital non-conglomerate	AI-SVI	1,00	0,9978
	IHSG	1,00	0,9998
	Volatility	1,00	0,9978
Digital Conglomerate	AI-SVI	1,00	0,9977
	IHSG	1,00	0,9974
	Volatility	1,00	0,9996
Fintech	AI-SVI	1,00	0,9990
	IHSG	1,00	0,9987
	Volatility	1,00	0,9996

Source: Author's calculation using Stata (2025)

4.3.2. Addressing Heteroskedasticity

Given the volatile nature of daily stock return data, the risk of heteroskedasticity is inherent in financial time series. To address this, we use robust standard errors in the regression estimation to correct potential heteroskedasticity without requiring separate tests such as the Breusch–Pagan test. This approach ensures the validity of the standard error estimates even in the presence of residual variance inconsistency.

4.3.3. Use of Robust Regression

Robust regression is adopted to enhance the reliability of the coefficient estimates, particularly in the presence of outliers or violations of classical assumptions. While the estimated coefficients remain interpretable as in standard OLS, the robust standard errors provide better resistance to heteroskedasticity. This method strengthens the robustness of our findings, particularly in testing the significance of AI sentiment (AI_SVI) on stock returns.

4.4. Discussion

4.4.1. Conventional Banks

The regression results indicate that AI sentiment (AI_SVI) does not significantly affect stock returns of conventional banks. This aligns with the fact that AI adoption in traditional banks remains concentrated on back-end functions—such as risk management and compliance—rather than on customer-facing innovations. According to Ghose et al. (2024), most AI applications in banking are still at the proof-of-concept stage, thus lacking visibility to drive investor sentiment. This finding supports Bonaparte (2024), who showed that only firms with AI as a core business narrative exhibit stock sensitivity to AI sentiment. From the perspective of the semi-strong form Efficient Market Hypothesis (EMH), the market likely perceives internal AI initiatives in conventional banks as immaterial. Additionally, in line with the Capital Asset Pricing Model (CAPM), returns are primarily influenced by systematic risk rather than firm-specific innovations.

4.4.2. Independent Digital Banks

Although descriptive statistics show that independent digital banks posted the highest average daily returns, AI_SVI is not statistically significant in the regression model. This suggests that the return premium may be driven by speculative or short-term factors unrelated to AI sentiment. As noted by the World Bank (2023), digital transformation in emerging markets like Indonesia faces structural challenges, limiting effective AI adoption. In the EMH framework, markets respond only to economically meaningful information. Given the limited integration and public visibility of AI in these banks, sentiment does not yet translate into pricing relevance. The result aligns with Bonaparte (2024), where firms lacking strategic AI positioning show no reaction to sentiment shift.

4.4.3. Digital Banks under Conglomerates

AI sentiment also shows no significant effect in the digital conglomerate bank category. One explanation is that market valuation for these banks is still anchored to the financial strength and reputation of their parent groups rather than technological narratives. Ernst & Young (2023) highlight that, in uncertain environments, investor trust hinges on group-level governance and resilience. In this context, internal AI use has not become a central driver of valuation. CAPM assumptions further support the finding: market returns (proxied by IHSG) consistently explain stock performance better than firm-specific innovations. As in Bonaparte (2024), unless AI is positioned as a public-facing strategic asset, sentiment does not influence investor behavior.

4.4.4. Fintech Banks

In contrast, AI_SVI has a significant positive impact on stock returns of fintech-driven banks. This reflects strong investor response to firms where AI is deeply embedded in the business model. Preis et al. (2013) and Lui et al. (2022) found that public attention to technology trends—captured through search data—can shift investor behavior, particularly when innovations are visible and core to the firm's value proposition. Notably, Bank Neo Commerce (BBYB) and Bank Amar (AMAR) have adopted AI in customer interaction and credit scoring, reinforcing their strategic AI narratives. While CAPM remains relevant—IHSG consistently affects all bank categories—the fintech case highlights the limitations of traditional models in explaining sentiment-driven returns. The findings challenge the semi-strong EMH and lend support to behavioral finance theories, especially the investor sentiment model by Baker & Wurgler (2006). Fintech stocks, often viewed as high-growth and high-risk, tend to be more responsive to non-fundamental factors like digital sentiment.

To complement the regression findings and assess whether investor perceptions align with observed market behavior, the next section presents a survey of retail investors in Indonesia. This survey aims to capture how investors interpret the role of AI in banking and whether they view AI adoption as a material signal in their investment decisions. By integrating quantitative results with qualitative insights, this study seeks to provide a more comprehensive understanding of how AI sentiment influences the banking sector.

4.4.5. Investor Perceptions of AI Adoption in Banking

This study includes a survey of retail investors with experience in Indonesia's banking sector to complement the regression analysis. The purpose is to examine whether investor perceptions align with the empirical relationship between AI sentiment and stock returns. The survey is structured based on four bank categories: conventional, independent digital, digital under conglomerates, and fintech-driven banks. Each category includes Likert-scale statements that assess the extent to which investors are aware of, trust, and consider AI adoption in their investment decisions. Table 4 presents the survey items and corresponding references that reflect the conceptual basis for each bank category. As part of the final section, respondents were also asked to identify which bank category they believe has implemented AI most effectively. This comparative item helps capture investor judgment on the perceived success of AI strategies across bank types and reinforces the relevance of the regression results discussed earlier.

Table 4. Summary of Investor Survey Results. Source: Researcher (2025)

No.	Statement	Agree (%)	Neutral (%)	Disagree (%)
1	I am aware that conventional banks have adopted AI for internal operations.	0%	40%	60%
2	AI is not a key factor in my investment decisions regarding conventional banks.	100%	0%	0%
3	I am aware that independent digital banks have adopted AI, although the implementation is still limited.	40%	60%	0%
4	I do not yet see AI adoption as a strong reason to invest in independent digital banks.	36,7%	63,3%	0%
5	I prioritize the reputation of the parent group over AI when investing in digital conglomerate banks.	100%	0%	0%
6	AI is not yet a major growth driver in digital conglomerate banks, in my view.	26,7%	73,3%	0%
7	I recognize that fintech banks have integrated AI into their core services.	100%	0%	0%
8	AI-based innovations in fintech banks increase my confidence in their business prospects.	100%	0%	0%

Survey responses are consistent with the regression results across all bank categories. For conventional banks, 60% of respondents were unaware of AI adoption, and all agreed that AI was not a major factor in their investment decisions. This supports the insignificant effect of AI sentiment on stock returns, likely due to the limited, back-end nature of AI usage that lacks visibility to investors. In independent digital banks, 60% responded neutrally regarding AI adoption, and only 36.7% viewed it as a strong investment reason. This reflects the low strategic presence of AI in this category, reinforcing the regression outcome showing no significant sentiment effect. Digital conglomerate banks also showed alignment. All respondents prioritized the parent group's reputation over AI, and 73.3% did not view AI as a growth driver. These perceptions confirm that investor focus remains on group-level fundamentals, not technological innovation. Fintech banks revealed the clearest convergence. All respondents acknowledged AI integration into core services and believed it enhanced their investment confidence. This supports the regression finding that AI sentiment significantly affects returns when AI is central to the business model. When asked which bank category best implemented AI, 46.67% selected fintech banks, followed by independent digital banks (30%), conglomerates (20%), and conventional banks (3.33%). These preferences underscore that only visible and strategic AI adoption drives investor sentiment. This pattern aligns with both the regression results and investor perceptions discussed earlier, reinforcing the conclusion that markets respond positively to AI sentiment only when the innovation is perceived as real, relevant, and directly linked to a firm's value proposition.

5. Conclusions

This study investigates whether public attention toward artificial intelligence (AI), as measured by a correlation-weighted Google Trends index (AI-SVI), influences stock returns in Indonesia's banking sector. By segmenting banks into four categories—conventional, digital under conglomerates, independent digital, and fintech-driven—the analysis captures the heterogeneous impact of AI sentiment across varying institutional structures and levels of digital maturity. Empirical findings reveal that AI-SVI significantly affects the stock returns of fintech-driven banks, but not other bank types. This suggests that investor sentiment toward AI only translates into pricing relevance when the innovation is perceived as strategic, visible, and integral to a firm's value proposition. The Jakarta Composite Index (IHSG), as a market risk proxy, consistently explains return movements across all bank categories, reinforcing the relevance of systematic risk as per CAPM. Meanwhile, stock-specific volatility did not emerge as a significant factor. To validate the empirical results, a supplementary investor survey was conducted. The responses closely mirrored regression outcomes, with investors expressing clear confidence in AI-driven fintechs while showing skepticism or indifference toward AI adoption in other bank categories. These findings underscore the role of perceived visibility and narrative alignment in shaping how sentiment influences market valuation. Theoretically, the results contribute to sentiment-based asset pricing literature by showing that behavioral signals like AI-related search trends matter in emerging markets—albeit selectively. Practically, the AI-SVI index developed in this study offers a timely diagnostic tool for tracking sentiment shifts and potential valuation pressures in digitally evolving financial sectors. However, several limitations must be acknowledged. The use of Google Trends assumes that search activity reflects investor behavior, which may exclude institutional perspectives or algorithmic trading effects. The survey sample is limited in size and scope, restricting generalizability. Future research could incorporate larger-scale behavioral surveys, institutional investor interviews, or alternative sentiment proxies such as media tone and social media analytics to broaden insight into how digital innovation shapes market behavior.

References

Ayala, M. J., Gonzálvez-Gallego, N., & Arteaga-Sánchez, R. (2024). Google search volume index and investor attention in stock market: a systematic review. In *Financial Innovation* (Vol. 10, Issue 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s40854-023-00606-y

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bonaparte, Y. (2024). Artificial Intelligence in Finance: Valuations and Opportunities. *Finance Research Letters*, *60*. https://doi.org/10.1016/j.frl.2023.104851

Campbell, J. Y., & Shiller, R. J. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. In *Source: The Review of Financial Studies* (Vol. 1, Issue 3). https://www.jstor.org/stable/2961997

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, *28*(1), 1–32. https://doi.org/10.1093/rfs/hhu072

Da, Z., Engelberg, J., Gao, P., Hirshleifer, D., Hou, K., Hwang, B.-H., Israelsen, R., Jagannathan, R., Jennings, R., Lepori, G., Lou, D., Loughran, T., Schaumburg, E., & Schultz, P. (2011). In Search of Attention. In *THE JOURNAL OF FINANCE •: Vol. LXVI* (Issue 5). http://www.google.com/trends

Ernst & Young. (2023). *EY Global Financial Services Regulatory Outlook 2023*. https://www.ey.com/en_gl/insights/financial-services/global-financial-services-regulatory-outlook-2023

Fama, E. F. (1970). American Finance Association Efficient Capital Markets: A Review of Theory and Empirical Work. *Source: The Journal of Finance*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*, 3–25.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. In *Source: The Journal of Finance* (Vol. 47, Issue 2).

Ghose, R., Bantanidis, S., Master, K., Shah, R. S., Yu, Y., Sharma, P., Dilaj, K., Van Kooij, B., & Zajac, A. (2024). *AI in Finance - "Bot, Bank & Beyond."* https://www.citigroup.com/citi/citigps/

Hamadou, I., Yumna, A., Hamadou, H., & Jallow, M. S. (2024). Unleashing the power of artificial intelligence in Islamic banking: A case study of Bank Syariah Indonesia (BSI). *Modern Finance*, *2*(1), 131–144. https://doi.org/10.61351/mf.v2i1.116

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets THE VALUATION OF RISK ASSETS AND THE SELECTION OF RISKY INVESTMENTS IN STOCK PORTFOLIOS AND CAPITAL BUDGETS *. *The Review of Economics and Statistics*, *47*(1), 13–37.

Lui, A. K. H., Lee, M. C. M., & Ngai, E. W. T. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research*, *308*(1–2), 373–388. https://doi.org/10.1007/s10479-020-03862-8

Mossin, J. (1966). *Equilibrium in a Capital Asset Market* (Vol. 34, Issue 4).

Padungsaksawasdi, C., Treepongkaruna, S., & Brooks, R. (2019). Investor attention and stock market activities: New evidence from panel data. *International Journal of Financial Studies*, *7*(2). https://doi.org/10.3390/ijfs7020030

Preis, T., Moat, H. S., & Eugene Stanley, H. (2013). Quantifying trading behavior in financial markets using google trends. *Scientific Reports*, *3*. https://doi.org/10.1038/srep01684

Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302. https://doi.org/10.1016/j.jfineco.2011.12.001

Swamy, V., & Dharani, M. (2019). Investor attention using the Google search volume index – impact on stock returns. *Review of Behavioral Finance*, *11*(1), 55–69. https://doi.org/10.1108/RBF-04-2018-0033

World Bank. (2023). *DIGITAL PROGRESS AND TRENDS REPORT 2023*. https://documents1.worldbank.org/curated/en/099031924192524293/pdf/P180107173682d0431bf651fded74199f10.pdf

Appendix

A. Descriptive Statistic

Category	Variable	Mean	Std. Dev.	Min	Max
Conventional	Return	-0,00026	0,03254	-1,6111	0,18641
	Volatility	0,02098	0,02484	0,00443	0,20827
	IHSG	0,00009	0,00985	-0,06805	0,09704
	AI_SVI	-0,49542	0,23171	-1,26422	0,04915
Digital Non-Conglomerate	Return	0,00063	0,03957	-0,2862	0,22314
	Volatility	0,00253	0,04094	-0,09138	0,00771
	IHSG	0,00015	0,00783	-0,04515	0,0344
	AI_SVI	0,23403	0,08475	-0,01288	0,52879
Digital Conglomerate	Return	0,00031	0,05056	-1,61631	0,32277
	Volatility	0,03989	0,0304	0	0,21554
	IHSG	0,00009	0,00985	-0,06805	0,09704
	AI_SVI	-0,46849	0,15828	-0,97078	0
Fintech	Return	-0,00055	0,0449	-0,14981	0,22445
	Volatility	0,04168	0,01963	0,00575	0,12702
	IHSG	0,00015	0,00783	-0,04515	0,0344
	AI_SVI	-0,7113	0,23538	-1,39081	0

B. Investor Perception Survey Questions by Bank Category. Source: Author (2025)

No.	Statement	Bank Category	References
1	I am aware that conventional banks have adopted AI, although its use is mainly for internal purposes such as risk management and operational efficiency.	Conventional Bank	Ghose et al. (2024)
2	AI is not a major factor I consider when making investment decisions in conventional bank stocks.	Conventional Bank	Ghose et al. (2024)
3	I am aware that independent digital banks have started using AI, but its implementation is not yet widely reflected in the services I experience as an investor.	Independent Digital Bank	World Bank (2023); Ghose et al. (2024)
4	I do not yet view AI implementation as a strong reason to invest in independent digital banks.	Independent Digital Bank	Bonaparte (2024)
5	I am aware that digital banks under conglomerates have adopted AI, but their group reputation and financial strength influence my investment decisions more than innovation.	Digital Conglomerate Bank	Ernst & Young (2023)
6	Although AI is used by digital conglomerate banks, I do not yet see it as a key driver of growth that would affect stock prices.	Digital Conglomerate Bank	Bonaparte (2024)

No.	Statement	Bank Category	References
7	I recognize that fintech banks integrate AI into their core services, such as personalized products and lending systems.	Fintech Bank	Lui et al. (2022); Ghose et al. (2024)
8	Visible AI-based innovations in fintech banks' services increase my confidence in their business prospects.	Fintech Bank	Preis et al. (2013); Bonaparte (2024)