Eduvest – Journal of Universal Studies
Volume 5, Number 9, September, 2025
p- ISSN 2775-3735- e-ISSN 2775-3727

Investor Sentiment Dynamics and Market Volatility in Indonesia: Hybrid Approach Using GARCH-Midas and Machine Learning

Lina Denita Siagian, Willem Makaliwe
Universitas Indonesia, Indonesia
Email: lina_denita@ui.ac.id, willem_makaliwe@ui.ac.id

ABSTRACT

The Indonesian stock market, represented by the Jakarta Composite Index (IHSG), experiences significant volatility influenced by both domestic and global macroeconomic factors as well as investor sentiment. This study investigates the impact of key macroeconomic variables and investor sentiment indicators, such as the Consumer Confidence Index (CCI) and Trading Volume Activity (TVA), on IHSG volatility. The research applies the GARCH-MIDAS model to capture long-term macroeconomic effects and integrates machine learning techniques, Extreme Gradient Boosting (XGBoost) for short-term volatility prediction. Monthly data on macroeconomic variables and sentiment indicators are combined with daily IHSG return data. Performance metrics like Mean Square Error are used to compare the forecast with realized volatility. The findings show that macroeconomic variables, particularly Inflation and Exchange Rates, significantly affect IHSG volatility, while sentiment indicator CCI play crucial roles and demonstrated the highest predictive power. The hybrid GARCH-MIDAS-XGBoost model outperformed the traditional GARCH-MIDAS, reducing MSE by approximately 20% and improving MAE by 15% during volatile periods. The model also excelled in predicting volatility spikes, especially during market turbulence. This study confirms that both macroeconomic variables and investor sentiment indicators, especially CCI, significantly impact stock market volatility. The hybrid model improves forecasting accuracy, offering valuable insights for investors and policymakers navigating market risks.

KEYWORDS *stock market volatility, GARCH-MIDAS, investor sentiment, machine learning, macroeconomics*

INTRODUCTION

The stock market plays a pivotal role in a nation's economy by enabling firms to raise capital and offering investment opportunities to the public. In Indonesia, the *Jakarta Composite Index* (IHSG) serves as the primary gauge of stock market performance, reflecting overall market dynamics and investor sentiment (Al-Gamrh et al., 2020; Alsmady, 2023; Dewi et al., 2020; Inci & Lagasse, 2019; Soewignyo & Soewignyo, 2015; Tangngisalu et al., 2023). However, the IHSG frequently exhibits significant volatility, influenced by a mix of domestic and international factors, creating challenges for investors, policymakers, and researchers alike. Volatility signals market uncertainty, which can have substantial implications for investment behavior and economic stability (Cui et al., 2023; Li et al., 2024; Riso & Vacca, 2024; Song et al., 2023; Stürmer, 2018; Virk et al., 2024).

Figure 1 presents the historical movements of the IHSG, illustrating notable fluctuations during several global and local crisis periods, such as the Asian financial crisis in the late 1990s, the global financial crisis of 2008, the Covid-19 pandemic, and geopolitical tensions including the US-China trade war and the Russia-Ukraine conflict. These episodes highlight how macroeconomic shocks and geopolitical events contribute to heightened market uncertainty and volatility. Understanding these factors is critical for investors to manage risk effectively.

Figure 1. Historical Trends of the Jakarta Composite Index

Several macroeconomic variables directly affect stock market volatility. Inflation, interest rates, and exchange rates are among the primary determinants that shape market expectations and investor behavior. For instance, rising inflation can erode purchasing power, dampen economic growth prospects, and increase uncertainty, thereby amplifying stock price fluctuations. Similarly, changes in interest rates influence the cost of capital, while exchange rate movements affect the competitiveness of firms, both impacting stock valuations (Imsar & Siregar, 2023; Januardi, 2022; Saputro & Meirinaldi, 2021; Viphindrartin, 2021; Wahyuni & Azhari, 2022).

Investor sentiment also plays a crucial role in driving market volatility. Sentiment indicators such as the *Consumer Confidence Index* (CCI) and *Trading Volume Activity* (TVA) provide insights into market psychology. The CCI reflects consumer optimism or pessimism regarding economic prospects, influencing investment decisions (Ayu Arghi Prameshti & Kurniasih, 2019; Kvamvold & Lindset, 2016; Rachman & Wijayanto, 2021; Shen et al., 2017). Meanwhile, TVA measures stock trading volumes, serving as a proxy for liquidity and investor engagement. Higher trading volumes during rising prices often indicate bullish sentiment, while declining volumes can presage reversals, contributing to increased volatility (Husnan, 2015).

Modeling stock market volatility faces challenges due to the mismatch in data frequency between daily stock prices and lower-frequency macroeconomic variables, such as monthly or quarterly indicators. Traditional models like GARCH require consistent data frequencies, limiting their capacity to incorporate macroeconomic influences effectively. The GARCH-MIDAS model overcomes this by integrating high-frequency stock returns with low-frequency macroeconomic data, capturing both short-term fluctuations and long-term effects on volatility (Engle et al., 2013; Ghysels et al., 2006).

Empirical studies have highlighted the significant role of macroeconomic factors in stock volatility. Schwert (1989) linked volatility with bond yields, interest rates, and industrial production, while Glosten et al. (1993) emphasized the impact of short-term interest rates on future variance. However, conventional models often rely on data transformations like aggregation or interpolation, which can cause information loss and biased forecasts (Nobre and Neves, 2019; Dieppe et al., 2021). These models also struggle to separate volatility into long- and short-term components.

GARCH-MIDAS addresses these issues by providing a flexible framework that captures complex volatility dynamics, including structural breaks (Wang and Ghysels, 2015). Global applications have confirmed its effectiveness; for example, Yu et al. (2021) found that global economic policy uncertainty significantly affects stock volatility in emerging markets, including Indonesia.

Previous studies, such as those by Aminda et al. (2021) and Riso et al. (2024), have demonstrated the impact of inflation, interest rates, and exchange rates on stock market volatility. However, these studies primarily focused on traditional GARCH models, which fail to adequately capture long-term effects due to the mismatch in data frequencies.

This study aims to propose a hybrid GARCH-MIDAS approach enhanced with machine learning (*XGBoost*) to improve volatility forecasting for the *Jakarta Composite Index*. This combination captures nonlinear residual patterns, offering better predictive accuracy and valuable insights for investors and policymakers managing market risks amid economic uncertainty. The findings provide valuable guidance for investors and policymakers to manage risk more effectively and make informed decisions amidst market uncertainty. The study contributes to financial econometrics by offering an advanced modeling approach and emphasizing the importance of integrating macroeconomic and sentiment factors into volatility forecasting models.

RESEARCH METHOD

This study utilizes secondary data collected from various sources to analyze the volatility of the *Jakarta Composite Index* (IHSG) in Indonesia. The data encompass daily stock prices and macroeconomic variables, which are crucial for understanding the dynamics influencing stock market performance, as presented in Table 1. The selection of variables includes *Trading Value Asset* (TVA), *Consumer Confidence Index* (CCI), interest rates, inflation rates, and the USD/IDR exchange rate.

Data on these macroeconomic variables are sourced from the IDX database and *Statistics Bank Indonesia*, ensuring credibility and relevance. The sample period for this analysis runs from January 2008 to December 2021, with in-sample periods from January 2008 to December 2019 and hold-out periods from January 2020 to December 2021. This timeframe was chosen to ensure the availability of comprehensive data across all variables, thereby avoiding gaps and ensuring that the results accurately reflect contemporary market patterns.

The daily stock price data for the IHSG were gathered from the IDX database, which provides extensive information on the performance of the Indonesian stock market. The monthly data for TVA, CCI, interest rates, inflation rates, and the USD/IDR exchange rate were also obtained from reliable sources, allowing for a robust analysis of the factors influencing stock market volatility in Indonesia.

Table 1: Summary of variables used in the study and their sources

Variables	Description	Frequency	No of obs	Data source
Stock returns IHSG	Composite Stock Price Index	Daily	4199	IDX database
TVA	IHSG Trading Value Asset	Monthly	207	IDX database
CCI	Indonesia Customer Confidence Index	Monthly	207	Statistics Bank Indonesia
Interest Rate	Indonesia Overnight Index Average	Monthly	207	Statistics Bank Indonesia
Inflation	Indonesia Inflation Rate	Monthly	207	Statistics Bank Indonesia
USD/IDR	Dollar USA – Rupiah Indonesia	Monthly	207	IDX database

Augmented Dickey-Fuller (ADF) Stationarity Test

The ADF test is conducted on the dataset to determine the existence of a unit root in the variables. This unit root test is performed on the response variable (stock returns of the *IHSG*) and the explanatory variables: *Trading Value Asset* (TVA), *Consumer Confidence Index* (CCI), interest rates, inflation rates, and the USD/IDR exchange rate (EXR). The null hypothesis of the test posits that the series has a unit root, indicating that it is non-stationary.

Heteroscedasticity Test

A heteroscedasticity test is essential to ensure that the regression can consistently predict the dependent variable across all independent variables. *Homoscedasticity*, the condition where the variance of the errors is constant across all levels of the independent variables, is necessary to guarantee efficient estimators of our parameters. Violations of homoscedasticity can lead to inefficient parameter estimates and affect the validity of t and F statistics used for inference. Therefore, it is crucial to test for heteroscedasticity to confirm the robustness of the regression model and ensure reliable statistical conclusions. Null Hypothesis (H0): The variance of the errors is constant across all levels of the independent variables (homoscedasticity).

Alternative Hypothesis (H1): The variance of the errors is not constant across all levels of the independent variables (heteroscedasticity).

Normality Test

The *Jarque-Bera* (JB) test was adopted to assess the normality of the stock returns dataset. According to the properties of a normal distribution, only the first two moments—mean and variance—completely describe the distribution. In statistical distributions, the third and fourth moments are typically measured by skewness and kurtosis.

Null Hypothesis (H0): The stock returns dataset follows a normal distribution.

Alternative Hypothesis (H1): The stock returns dataset does not follow a normal distribution.

The Lagrange Multiplier (LM) Test for ARCH Disturbances The GARCH family of models requires the presence of ARCH effects in the series, which is a fundamental condition. In this study, the ARCH-LM test is employed to assess the existence of ARCH effects in the ARMA residuals (mean equation). By analyzing the difference between the actual and expected values—referred to as the residuals of the mean equation—the square of these residuals is used to determine conditional heteroscedasticity.

The LM test, proposed by Engle (1982), involves regressing the squared residuals on past lagged squared residual values. The null and alternative hypotheses for the LM test are as follows:

Null Hypothesis (H0): There are no ARCH effects in the residuals of the time series model.

$$H_0: \psi_1 = \psi_2 = \cdots = \psi_q = 0$$

Alternative Hypothesis (H1): There are ARCH effects in the residuals of the time series model. At least one of the coefficients of the lagged squared residuals is different from zero.

$$H_1: At\ least\ one\ \psi_i \neq 0\ for\ i = 1,2,\ldots,q$$

The LM test statistic can be derived from the coefficient of determination R^2 of the regression. Specifically, the ARCH-LM statistic, denoted as LM(q), is given by:

$$LM(q) = TR^2$$

where T is the number of observations in the series. If the null hypothesis of no conditional heteroscedasticity holds, the statistic follows an asymptotic χ_q^2 distribution. Large values of the test statistic suggest that H_0 is false, indicating potential ARCH effects in the residuals. In such cases, it may be beneficial to consider fitting an ARCH or ARCH-type model to the residuals.

Additionally, an F-version of the statistic may be utilized for potentially better small sample properties, represented as follows:

$$FLM = \frac{R^2}{1 - R^2} \cdot \frac{T - p - q - 1}{q}$$

where FLM follows an $F(q, T - p - q - 1)$ distribution.

Ljung-Box Test

The Ljung-Box test evaluates the presence of autocorrelation in the squared residuals based on their immediate preceding values. The test statistic is calculated using the sample size and the estimated autocorrelations of the residuals. Under the null hypothesis of no autocorrelation, the test statistic follows a chi-square distribution with degrees of freedom equal to the number of lags being tested. The null hypothesis of no autocorrelation is rejected if the calculated value of the test statistic exceeds the critical value from the chi-square distribution.

Model Evaluation

Akaike Information Criteria (AIC): AIC is one of the first widely accepted model selection criteria. It extends the maximum likelihood principle, allowing for the estimation of model parameters once the model structure is understood. AIC helps in identifying the model that best fits the data while penalizing for the number of parameters to prevent overfitting.

Bayesian Information Criteria (BIC): BIC is developed within the Bayesian framework for selecting the best model from a set of candidate models. It evaluates models based on the likelihood function, considering their asymptotic properties. BIC also incorporates a penalty for the number of parameters, with a stronger penalty than AIC, which helps in selecting simpler models when the sample size is large.

These criteria are essential for model comparison and selection, ensuring that the chosen model balances goodness of fit with complexity.

GARCH Model

Using the ARMA-GARCH model, the mean equation is a linear ARMA (p, q) model that is univariate and comprises an autoregressive and moving average component. The combination of the ARMA and GARCH models has been widely used to model both fluctuating stationary and non-stationary effects in financial and economic time series. The general ARMA (p, q) model is defined as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$

where y_t is the value of the time series at time t, ϕ_0 is the model intercept, ε_t is the white noise process at time t, ϕ_i are the parameters of the autoregressive part of the model (for i=1,2,…,p) and θ_j are the parameters of the moving average part of the model (for j=1,2,…,q).

The general form of the GARCH (p, q) model consists of the mean and variance equations. The mean equation of the GARCH (p, q) model is expressed as:

$$y_t = \mu + \epsilon_t$$

where $\epsilon_t = \sigma_t z_t$ and $z_t \sim \mathrm{N}(0,1)$.

The variance equation of the GARCH (p, q) model is written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where σ_t^2 is the conditional variance of ϵ_t at time t, α_0 is the constant term, α_i are the coefficients of the lagged squared error terms (for i=1,2,…,p), and β_j are the coefficients of the lagged conditional variances (for j=1,2,…,q).

To ensure non-negativity and that the value of the conditional variance is always non-negative, the following conditions must be met:

$$\alpha_0 > 0$$
$$\alpha_i \geq 0 \; for \; all \; i$$
$$\beta_j \geq 0 \; for \; all \; j$$

The ARMA-GARCH framework is a standard approach for analyzing volatility in financial time series, providing valuable insights into market behavior and risk management.

GARCH MIDAS

In this study, we employed a multiplicative two-class volatility component

GARCH-MIDAS model introduced by Engle et al. (2013). The GARCH-MIDAS technique models returns as the product of a unit variance GARCH model, which captures short-term volatility swings, and an explanatory variable based on components that illustrate macroeconomic changes over time. This model combines short-run GARCH (1, 1) high-frequency volatility with low-frequency macroeconomic variables, managed by the MIDAS regression introduced by Ghysels et al. (2007).

The GARCH-MIDAS framework incorporates lagged values of stock returns at different frequencies, allowing for a comprehensive representation of the underlying volatility dynamics (Yao and Li, 2023). This feature enables the model to better capture short-term and long-term dependencies in the data, making it particularly suitable for predicting stock return time series with irregularly spaced observations (Salisu et al., 2020).

The daily stock return is calculated as:

$$r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1}$$

The daily return is assumed to follow the process:

$$r_{i,t} = \mu + T_t g_{i,t} \epsilon_{i,t}\,, \quad \forall_i = 1,2,\ldots,N_t \qquad (2.14)$$

where $\epsilon_{i,t} \sim \mathrm{N}(0,1)$, $r_{i,t}$ represents the return of stock i at time t, μ is the constant mean stock return, T_t is the long-term component of volatility at time t, $g_{i,t}$ represents the short-term (GARCH) component of volatility for stock i at time t, and $\epsilon_{i,t}$ is the error term for stock i at time t.

From (2.14), squaring both sides yields:

$$\left(r_{i,t} - \mu\right)^2 = T_t g_{i,t} \epsilon_{i,t}^2$$

Dividing both sides by T_t gives:

$$g_{i,t}\epsilon_{i,t}^2 = \frac{\left(r_{i,t} - \mu\right)^2}{T_t}$$

The short-term component of the volatility, $g_{i,t}$, in the GARCH-MIDAS framework is typically modeled using a GARCH(1,1) process:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i,t-1} - \mu\right)^2}{T_t} + \beta g_{i-1,t}$$

where $(1 - \alpha - \beta) = \omega$ and β and α are GARCH and ARCH parameters, respectively, such that $\beta \geq 0$, $\alpha > 0$, and $\alpha + \beta \leq 1$.

The long-term component T_t is modeled as:

$$\ln T_t = m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{t-k}$$

with

$$T_t = \exp\left(m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{t-k}\right)$$

where m is a constant term, θ quantifies the effect of low-frequency factors on long-term volatility, and $\phi_k(\omega_1, \omega_2)$ represents the weighting function applied to the lagged values of the explanatory variables.

GARCH-MIDAS model estimation process

In the GARCH-MIDAS model, the parameters are estimated using the maximum likelihood estimation (MLE) method. The goal of MLE is to determine the parameter values that maximize the likelihood of observing the actual data given the model. The log-likelihood function is estimated by finding the parameters that maximize it.
Given the equation:

$$r_{i,t} = \mu + T_t g_{i,t} \epsilon_{i,t}\,, \quad \forall_i = 1,2,\ldots,N_t$$

the log-likelihood function for the restricted version is represented as:

$$\mathrm{L} = \ln L(\mu,\alpha,\beta,\theta,\omega)$$

Assuming the errors $\epsilon_{i,t}$ are normally distributed, the conditional density is given by:

$$f\left(r_{i,t}\middle|F_{t-1}\right) = \frac{1}{\sqrt{2\pi T_t g_{i,t}}}\exp\left(-\frac{\left(r_{i,t}-\mu\right)^2}{2T_t g_{i,t}}\right)$$

The log-likelihood function for a sample of T observations is expressed as:

$$L = \sum_{t=1}^{T}\sum_{i=1}^{N_t}\log f\left(r_{i,t}\middle|F_{t-1}\right)$$

Substituting the density function into the log-likelihood function yields:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left[\log(2\pi) + \log(T_t g_{i,t}) + \frac{\left(r_{i,t}-\mu\right)^2}{T_t g_{i,t}}\right]$$

The parameters μ,α,β,m,θ,ω are estimated by maximizing the log-likelihood function using numerical optimization techniques.

Hybrid GARCH-MIDAS Combined with Machine Learning

The Hybrid GARCH-MIDAS model integrates GARCH volatility modeling with macroeconomic data sampled at different frequencies (e.g., monthly data for daily volatility) to capture long-term macroeconomic effects on volatility. In this study, we enhance the model by incorporating XGBoost, a decision-tree-based machine learning algorithm, to predict residuals from the GARCH-MIDAS model.

The residuals, defined as the difference between actual returns and GARCH-MIDAS predicted volatility, serve as targets for XGBoost, which models nonlinear patterns unexplained by GARCH-MIDAS. The XGBoost objective function minimizes squared errors with a regularization term to control complexity:

$$\mathcal{L}(\mathrm{f}) = \sum_{i=1}^{n}\left(y_i - f(x_i)\right)^2 + \lambda\sum_{j=1}^{m}\left(\left\|w_j\right\|^2\right)$$

The final volatility forecast combines the GARCH-MIDAS prediction with the XGBoost-predicted residuals, improving accuracy and robustness. This hybrid approach leverages GARCH-MIDAS for macroeconomic-driven long-term volatility and XGBoost for capturing complex residual structures. Further enhancements can be achieved by adding macroeconomic variables and applying advanced regularization during training.

RESULT AND DISCUSSION

ARCH-LM Test

To determine the presence of conditional heteroscedasticity in the IHSG return series, the ARCH-LM test was applied to the residuals of both the selected ARMA and ARMA-GARCH models. This test assesses whether the variance of the residuals is autocorrelated, which would indicate time-varying volatility and justify the use of GARCH-family models.

As shown in Table 4, the ARCH-LM test applied to the residuals of the ARMA(0,2) model yields a test statistic of 5.3724 with a p-value of 0.0205, which strongly rejects the null hypothesis of no ARCH effects. This indicates the presence of conditional heteroscedasticity and volatility clustering in the IHSG return series that the ARMA(0,2) model alone fails to capture. In contrast, when the GARCH(2,1) model is fitted, the ARCH-LM test statistic dramatically decreases to 0.0605 with a non-significant p-value of 0.8058, indicating that the GARCH model effectively accounts for the conditional heteroscedasticity.

Table 2. Correlation Matrix of Macroeconomic Variables in Indonesia

	TVA	CCI	IR	INF	EXR
TVA	1	-0.1540575	-0.1642681	-0.306924	0.3627621
CCI	-0.1540575	1	-0.1400538	-0.1129263	-0.1876624
IR	-0.1642681	-0.1400538	1	0.7497007	-0.4717209
INF	-0.306924	-0.1129263	0.7497007	1	-0.5226234
EXR	0.3627621	-0.1876624	-0.4717209	-0.5226234	1

Table 3: Lagrange-Multiplier and Box-Ljung Test Results

Model	ARCH LM Stat	ARCH P-Value	Box Q	Box P-Value
ARMA(0,2)	5.372431	0.0204574	9.982387	0.4420399
GARCH(2,1)	0.06046	0.8058	0.7102	0.3994

The Box-Ljung test conducted on the residuals of both models shows no evidence of significant serial correlation. For the ARMA(0,2) model, the Box Q statistic is 9.9824 with a p-value of 0.4420, and for the GARCH(2,1) model, the Box Q statistic is 0.7102 with a p-value of 0.3994. Both p-values exceed the 5% significance level, supporting the absence of significant autocorrelation in the residuals.

These results confirm the appropriateness of GARCH-type models, specifically the GARCH(2,1), for modeling volatility in the IHSG returns. The GARCH(2,1) model successfully captures volatility persistence and clustering that are not accounted for by the ARMA(0,2) model alone.

Fitting ARMA-GARCH Model

To determine the most appropriate volatility model for the Indonesian equity market, this study explored various ARMA(p,q) and GARCH(p,q) model combinations. The model selection was guided by information criteria—specifically the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)—to identify the best fitting specifications. As reported in Table 4, the ARMA(0,2) model yielded the lowest AIC (-18978.53) and BIC (-18954.53) among all ARMA configurations tested. This model captures the moving average components in the IHSG return series, implying that past shocks influence current market behavior.

Subsequently, various GARCH models were estimated using residuals from the ARMA(0,2) model. The results, shown in Table 6, reveal that the ARMA(0,2)-GARCH(1,2) specification provides the best fit based on minimum AIC (-6.62285) and BIC (-6.60677). This model captures both short-term shock impacts and moderate persistence in volatility, which is a common feature of financial time series data, especially in emerging markets like Indonesia.

Table 4. Results of Fitting

ARMA(p, q)	AIC	BIC	Best Fit
(0,0)	-18962	-18949.99	
(0,1)	-18965.56	-18947.56	
(0,2)	-18978.53	-18954.53	*
(0,3)	-18977.44	-18947.43	
(1,0)	-18964.79	-18946.78	
(1,1)	-18976.02	-18952.01	
(1,2)	-18977.99	-18947.98	
(1,3)	-18975.41	-18939.39	
(2,0)	-18977.35	-18953.35	

*Indicates the best fitted ARMA(p,q) model based on minimum AIC and BIC criteria.

Table 5. Results of Fitting ARMA(2,1)-GARCH(p,q) Models

GARCH(p, q)	AIC	BIC	Best Fit
(1,1)	-6.622296	-6.60823	
(1,2)	-6.622847	-6.606772	*
(1,3)	-6.622721	-6.604636	
(2,1)	-6.621626	-6.605551	
(2,2)	-6.622177	-6.604093	
(2,3)	-6.622051	-6.601957	
(3,1)	-6.620888	-6.602803	
(3,2)	-6.621431	-6.601337	
(3,3)	-6.621381	-6.599278	

*Indicates the best fitted ARMA-GARCH(p,q) model based on minimum AIC and BIC criteria.

The selection of the GARCH(1,2) model highlights the importance of including an additional lag of past squared residuals to better model the volatility clustering present in the IHSG returns. This finding validates the presence of asymmetric or persistent volatility effects, which are crucial for accurate risk modeling and forecasting. Together, the ARMA(0,2) and GARCH(1,2) combination forms a robust framework for capturing the dynamics of the Indonesian stock market and will serve as the benchmark model for subsequent comparisons with GARCH-MIDAS and machine learning-enhanced models in this study.

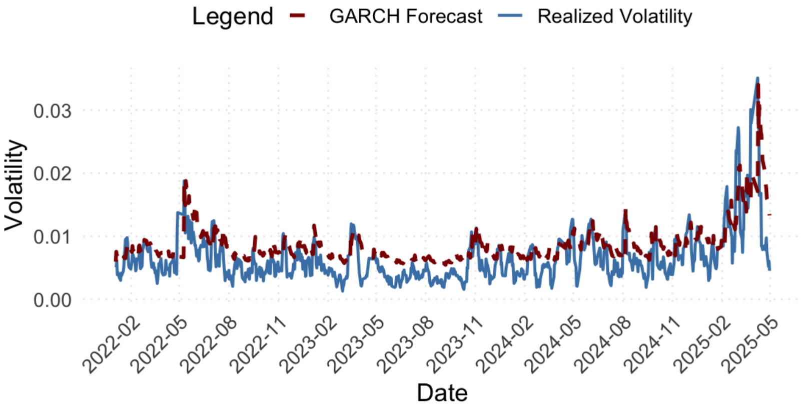

Figure 2. Historical Volatility Trends vs GACRH Forecasted

ARMA-GARCH Parameter Estimate Results

This section presents the estimated parameters of the fitted ARMA(0,2)-GARCH(1,2) model for the Indonesian stock market. As shown in Table 7, the coefficients were obtained without including any exogenous variables and were estimated using maximum likelihood under a normal distribution assumption. All model parameters are statistically significant at conventional levels, with the mean (μ) significant at the 0.1% level ($p = 0.000647$). The AR(1) term is significant at the 5% level ($p = 0.0121$), AR(2) at less than 0.1% ($p = 0.000197$), and MA(1) also significant at 5% ($p = 0.0143$), confirming the adequacy of the ARMA(0,2) structure in capturing the mean dynamics of the return series.

On the variance side, the model includes one ARCH term (α_1) and one GARCH term (β_1). Both variance equation parameters are highly significant (p-values = 0), indicating that volatility is influenced both by recent shocks (ARCH effect) and past variances (GARCH effect). The estimated ω (omega) is also significant ($p = 0.0125$), representing the constant term in the variance equation. The sum of α_1 and β_1 is 0.98224 (0.117128 + 0.865111), which is close to unity, confirming the presence of volatility persistence and clustering in the Indonesian stock market. This supports the appropriateness of using GARCH-type models to capture the conditional heteroscedasticity.

Further diagnostic tests such as the Nyblom stability test suggest that all estimated parameters are stable over time, and the Sign Bias test indicates the possible presence of asymmetric responses to past shocks, particularly in negative returns. These results underscore the robustness of the chosen ARMA(0,2)-GARCH(1,2) specification for modeling volatility dynamics in the Indonesian equity market.

Table 6. Parameter Estimates for Fitted ARMA(0,2)-GARCH(1,2) Model

Coefficient	Estimate	Std. Error	t-Value	p-Value
μ (Mean)	0.000411	0.00012	3.411	0.000647
AR(1)	0.490041	0.195218	2.5102	0.012065
AR(2)	-0.064366	0.017292	-3.7222	0.000197
MA(1)	-0.478331	0.195267	-2.4496	0.0143
ω (Omega)	0.000003	0.000001	2.4967	0.012537
α_1 (ARCH)	0.117128	0.013326	8.7897	0
β_1 (GARCH)	0.865111	0.014748	58.6604	0

Note: All parameters are statistically significant at the 5% level or better. The sum of ARCH and GARCH coefficients ($\alpha_1 + \beta_1 + \beta_2 = 0.98224$) indicates strong volatility persistence.

GARCH-MIDAS Parameter Estimate Results

This study estimated several GARCH-MIDAS models to analyze the impact of macroeconomic variables on long-term volatility in the Indonesian stock market. Macroeconomic indicators such as Trading Volume Activity (TVA), Consumer Confidence Index (CCI), Interest Rate (IR), Inflation (INF), and Exchange Rate (EXR) were incorporated with a 36-month lag structure. The short-run GARCH parameters remained significant across models, confirming persistent short-term volatility. Among the macro variables, the Consumer Confidence Index (CCI) showed the best forecasting performance with low HMSE (0.0077) and relatively low HMAE (0.1800), suggesting strong predictive power on long-term volatility.

The standard GARCH-MIDAS model outperformed others in terms of loss metrics (HMSE = 0.0316, HMAE = 0.1364), while models based on TVA and Inflation had higher error rates. The Exchange Rate (EXR) model, despite low HMSE and HMAE, showed instability and is thus less reliable. Overall, all macro-based GARCH-MIDAS models provided better heteroskedasticity-adjusted loss values (HMSE and HMAE) compared to the standard GARCH, supporting the value of including macroeconomic factors in volatility modeling. Table 8 compares loss metrics of each GARCH-MIDAS specification versus the standard GARCH model. Notably, all macro-based models outperformed GARCH in terms of heteroskedasticity-adjusted losses (HMSE and HMAE).

Table 7. Loss Function Comparison Table

Macro	MSE	MAE	HMSE	HMAE
GARCH MIDAS	0.0000026	0.0011	0.0316	0.1364
GM-TVA	0.000023	0.0042	0.1432	0.4683
GM-CCI*	0.000005	0.0016	0.0077	0.1800
GM-IR	0.000020	0.0036	0.0135	0.3939
GM-INF	0.000217	0.0103	0.8247	1.1387
GM-EXR*	0.000002	0.0010	0.0053	0.1160

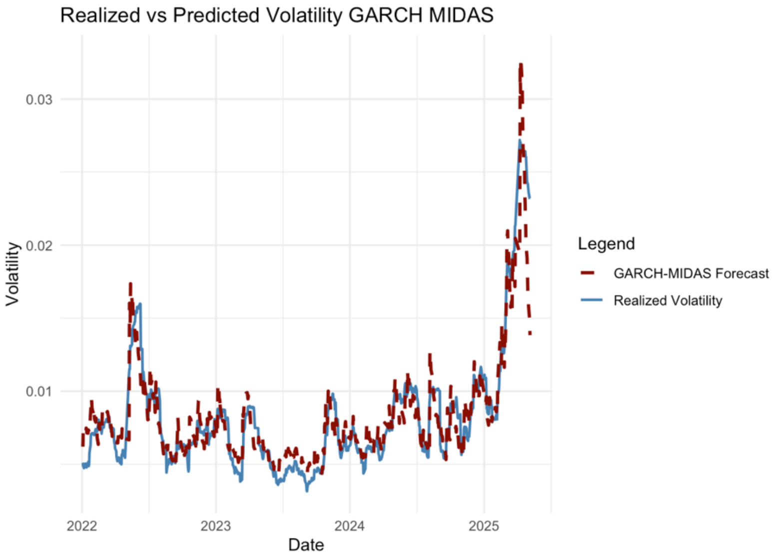

Figure 3. Historical Volatility Trends vs GARCH-MIDAS Forecasted

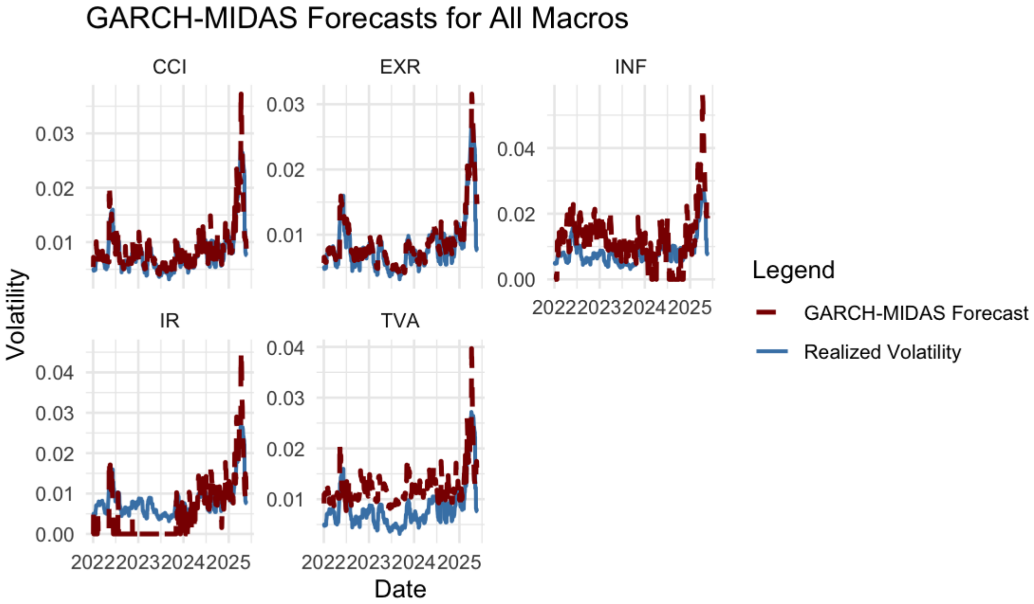

Figure 4. Historical Volatility Trends vs GARCH-MIDAS Forecasted (All Macro)

GARCH-MIDAS + XGBoost Parameter Estimate Results

To further improve the predictive accuracy of volatility forecasts, this study integrates a deep learning framework by applying XGBoost to the estimated GARCH-MIDAS volatility series. This approach aims to capture potential nonlinearities and complex interactions between the macroeconomic lag features and the conditional volatility component from the GARCH-MIDAS model. The forecast performance of the XGBoost model for each macroeconomic variable is summarized in Table 9.

Among the five macroeconomic variables examined, the Consumer Confidence Index (CCI) emerged as the best predictor within the XGBoost framework, achieving the lowest HMSE (0.24613) and HMAE (0.46308). This indicates that the model effectively extracts meaningful patterns from historical CCI data to capture volatility dynamics, highlighting the importance of sentiment-based indicators in modeling market uncertainty. Interestingly, the Exchange Rate (EXR) model, despite recording the lowest loss values across most metrics (HMSE = 0.1775, HMAE = 0.37225), showed relatively high heteroskedasticity-adjusted losses, suggesting some instability or nonlinear complexity when combined with GARCH-MIDAS. Overall, these results demonstrate the enhanced capability of XGBoost in extracting nonlinear relationships in volatility forecasting when integrated with macroeconomic information.

Table 8. GARCH-MIDAS + XGBoost Forecast Loss Metrics

Macro	MSE	MAE	HMSE	HMAE
GM - XGBoost	1.60E-05	0.0032	0.26452	0.49045
GM-XGB-TVA	1.56E-05	0.00297	0.25884	0.45475
GM-XGB-CCI*	1.48E-05	0.00302	0.24613	0.46308
GM-XGB-IR	5.42E-05	0.00605	0.89902	0.9265

Macro	MSE	MAE	HMSE	HMAE
GM-XGB-INF	3.82E-05	0.0051	0.6335	0.78187
GM-XGB-EXR*	1.07E-05	0.00243	0.1775	0.37225

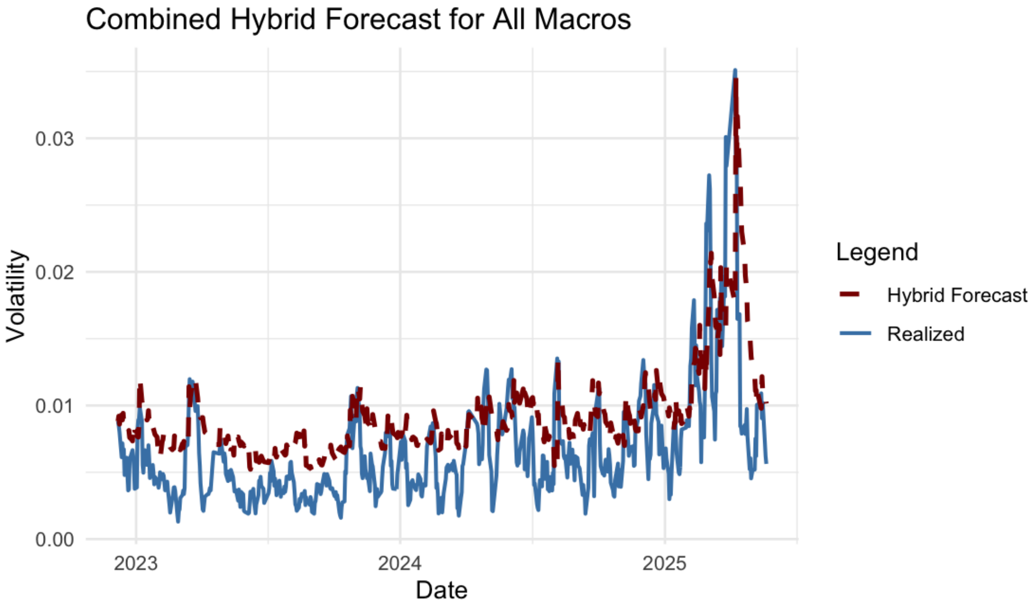

Figure 5. Historical Volatility Trends vs GARCH-MIDAS-XGBoost Forecasted

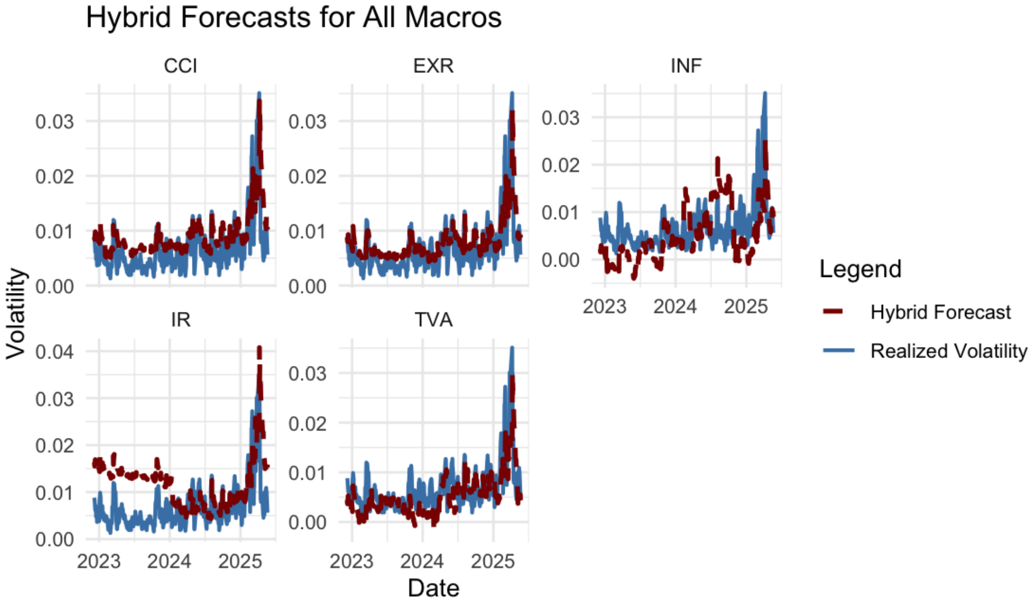

Figure 6. Historical Volatility Trends vs GARCH-MIDAS-XGBoost Forecasted (All Macros)

CONCLUSION

This study investigates the relationship between macroeconomic variables and stock market volatility in Indonesia, focusing on the *Jakarta Composite Index* (IHSG). Using ARMA-GARCH, GARCH-MIDAS, and GARCH-MIDAS enhanced by *XGBoost* models, the findings show that macroeconomic factors significantly affect financial market behavior. The ARMA(0,2)-GARCH(1,2) model was identified as the best fit for capturing short-term shocks and volatility persistence. The GARCH-MIDAS model, incorporating monthly macroeconomic variables, highlighted the *Consumer Confidence Index* (CCI) and Exchange Rate (EXR) as key predictors, with CCI showing the best forecasting performance. The integration of *XGBoost* with GARCH-MIDAS significantly improved forecast accuracy, especially when using CCI as an input. The study suggests that macroeconomic stability, particularly inflation control and consumer sentiment, is crucial for mitigating stock market volatility, with practical implications for policymakers, financial regulators, and investors. Policymakers are advised to monitor these indicators to maintain market stability, while investors can benefit from incorporating macroeconomic fundamentals into risk assessment models. Academically, this study demonstrates the value of hybrid modeling approaches, and future research could explore additional macroeconomic variables and more advanced machine learning techniques. The findings contribute to financial econometrics and offer actionable guidance for enhancing market resilience.

REFERENCES

Al-Gamrh, B., Ku Ismail, K. N. I., Ahsan, T., & Alquhaif, A. (2020). Investment opportunities, corporate governance quality, and firm performance in the UAE. *Journal of Accounting in Emerging Economies*, *10*(2), 269-291. https://doi.org/10.1108/JAEE-12-2018-0134

Alsmady, A. A. (2023). The moderating role of audit quality between earning management and sustainable investment opportunities: Evidences from gulf cooperation council countries. *International Journal of Applied Economics, Finance and Accounting*, *16*(1), 23-37. https://doi.org/10.33094/ijaefa.v16i1.874

Aminda, D., Cahyadi, R., & Pramono, B. (2021). Stabilitas makroekonomi dan pengaruhnya terhadap sentimen pasar modal di Indonesia. *Jurnal Ekonomi dan Bisnis Indonesia*, *36*(2), 89-101.

Ayu Arghi Prameshti, G., & Kurniasih, A. (2019). The effect of fundamental factors on stock returns at insurance companies on the Indonesia Stock Exchange. *Research Journal of Applied Sciences*, *14*(3), 76-83. https://doi.org/10.36478/rjasci.2019.76.83

Cui, Y., Zheng, H., & Yuan, Y. (2023). Sentiment, herding and volatility forecasting: Evidence from GARCH-MIDAS approach. *Fluctuation and Noise Letters*, *22*(2), Article 2350015. https://doi.org/10.1142/S0219477523500153

Dewi, I. G. A. S., Endiana, I. D. M., & Arizona, I. P. E. (2020). Pengaruh leverage, investment opportunity set (ios), dan mekanisme good corporate covernance terhadap kualitas laba pada perusahaan manufaktur di bursa efek Indonesia. *Kumpulan Hasil Riset Mahasiswa Akuntansi (KHARISMA)*, *2*(1), 132-147.

Dieppe, A., Legrand, R., & van Roye, B. (2021). The BEAR toolbox. *European Central Bank Working Paper Series*, No. 2934.

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *The Review of Economics and Statistics*, *95*(3), 776-797.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, *131*(1-2), 59-95.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779-1801.

Husnan, S. (2015). *Dasar-dasar teori portofolio dan analisis sekuritas* (5th ed.). UPP STIM YKPN.

Imsar, I., & Siregar, I. A. (2023). Stabilitas ekonomi makro dalam perspektif ekonomi Islam: Teori dan praktek. *Jurnal AKTUAL*, *21*(2), 115-128. https://doi.org/10.47232/aktual.v21i2.408

Inci, A. C., & Lagasse, R. (2019). Cryptocurrencies: Applications and investment opportunities. *Journal of Capital Markets Studies*, *3*(2), 99-112. https://doi.org/10.1108/JCMS-05-2019-0032

Januardi, J. (2022). Stabilitas ekonomi pada pasar induk Palembang perspektif mikro dan makro. *Prosiding Seminar Nasional Ekonomi*, *2*(1), 45-58.

Kvamvold, J., & Lindset, S. (2016). Do dividend distributions affect stock returns? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2729284

Li, X., Ye, C., Bhuiyan, M. A., & Huang, S. (2024). Volatility forecasting with an extended GARCH-MIDAS approach. *Journal of Forecasting*, *43*(1), 158-175. https://doi.org/10.1002/for.3023

Nobre, J., & Neves, R. F. (2019). Combining principal component analysis, discrete wavelet transform and XGBoost to trade in the financial markets. *Expert Systems with Applications*, *125*, 181-194.

Rachman, A. N., & Wijayanto, A. (2021). Do fundamental and behavioral factors affect insurance company's stock returns? *Management Analysis Journal*, *10*(2), 156-167.

Riso, L., & Vacca, G. (2024). Sentiment dynamics and volatility: A study based on GARCH-MIDAS and machine learning. *Finance Research Letters*, *62*, Article 105178. https://doi.org/10.1016/j.frl.2024.105178

Saputro, G. E., & Meirinaldi, M. (2021). Pengaruh stabilitas makro ekonomi, stabilitas keamanan dan pertumbuhan industri strategis terhadap pertumbuhan ekonomi. *JURNAL EKONOMI*, *23*(1), 67-85. https://doi.org/10.37721/je.v23i1.757

Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, *44*(5), 1115-1153.

Shen, C. H., Bui, D. G., & Lin, C. Y. (2017). Do political factors affect stock returns during presidential elections? *Journal of International Money and Finance*, *77*, 18-38. https://doi.org/10.1016/j.jimonfin.2017.07.019

Soewignyo, F., & Soewignyo, T. I. (2015). The influence of talent factors on business performance. *Issues in Social and Environmental Accounting*, *9*(1), 22-35. https://doi.org/10.22164/isea.v9i1.100

Song, Y., Tang, X., Wang, H., & Ma, Z. (2023). Volatility forecasting for stock market incorporating macroeconomic variables based on GARCH-MIDAS and deep learning models. *Journal of Forecasting*, *42*(1), 126-141. https://doi.org/10.1002/for.2899

Stürmer, K. (2018). Time-varying volatility persistence in a GARCH-MIDAS framework. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3258136

Tangngisalu, J., Halik, A., Marwan, & Jumady, E. (2023). Leverage analysis, investment opportunity set, and ownership of company value. *Journal of Law and Sustainable Development*, *11*(5), 892-908. https://doi.org/10.55908/sdgs.v11i5.992

Viphindrartin, S. (2021). Dampak makro ekonomi terhadap stabilitas keuangan di Indonesia. *Jurnal Manajemen Jayanegara*, *13*(1), 45-62. https://doi.org/10.52956/jmj.v13i1.27

Virk, N., Javed, F., Awartani, B., & Hyde, S. (2024). A reality check on the GARCH-MIDAS volatility models. *European Journal of Finance*, *30*(6), 523-548. https://doi.org/10.1080/1351847X.2023.2217220

Wahyuni, S., & Azhari, A. (2022). Volatilitas dan stabilitas pasar modal syariah: Indikator makro dan mikro ekonomi. *Jurnal SEKURITAS (Saham, Ekonomi, Keuangan Dan Investasi)*, *5*(2), 178-195. https://doi.org/10.32493/skt.v5i2.12556

Wang, Y., & Ghysels, E. (2015). GARCH-MIDAS models for cryptocurrency volatility forecasting. *Journal of Financial Econometrics*, *13*(4), 723-751.

Yu, L., Wang, S., & Lai, K. K. (2021). Global economic policy uncertainty and stock volatility: Evidence from emerging markets. *Economic Modelling*, *94*, 297-309.