JURNAL INFOTEL
VOL. 17, NO. 4, NOVEMBER 2025, PP. 696–715. DOI:10.20895/INFOTEL.V17I4.1408

RESEARCH ARTICLE

Forecasting the Stock Price of PT Unilever Indonesia Using the ARCH-GARCH Model with the Application of Kalman Filter

Sausan[1], Atika Ratna Dewi[2,*], and Aminatus Sa'adah[3]

[1,2]Data Science Study Program, Telkom University, Purwokerto Campus, Jl. DI Panjaitan No, 128, Purwokerto 53147, Central Java, Indonesia
[3]Informatics Engineering Study Program, Telkom University, Purwokerto Campus, Jl. DI Panjaitan No, 128, Purwokerto 53147, Central Java, Indonesia

*Corresponding email: atikad@telkomuniversity.ac.id

Received: July 07, 2025; Revised: September 01, 2025; Accepted: September 04, 2025.

Abstract: PT Unilever Indonesia experiences significant stock price volatility driven by both internal and external factors. This volatility underscores the need for accurate forecasting methods to support investment decision-making and risk management. This study aims to forecast the company's stock prices using ARCH-GARCH models, enhanced with the Kalman Filter to improve predictive performance. Daily historical stock price data from January 1, 2014, to December 31, 2024, were obtained from the `yfinance` library. The research methodology comprises several stages: literature review, data collection, exploratory data analysis, data pre-processing, forecast modeling, and evaluation. Among the evaluated models, the GARCH(1,2) with a skewed Student's error distribution was identified as the best-fitting model, achieving an AIC of -5.476981. The baseline forecast using the GARCH model yielded a MAPE of 49.47%, an RMSE of 45.56%, and an MAE of 37.16%. However, after integrating the Kalman Filter, the model's forecasting performance improved substantially, with MAPE decreasing to 6.04%, RMSE to 6.01%, and MAE to 5.02%. These findings indicate that the Kalman Filter effectively reduces noise, enables dynamic state updating, and enhances the model's adaptability to market fluctuations. The improvement underscores the value of incorporating dynamic filtering techniques into volatility modeling, thereby providing more reliable forecasts for investment and risk management.

Keywords: arch-garch, forecasting, kalman filter, PT Unilever Indonesia, stock price

---

1 Introduction

Stocks are a fundamental component of the capital market and among the most actively traded instruments on the stock exchange [1]. They enable companies to raise additional capital while offering investors opportunities to earn returns through dividends and capital gains. Stock prices are often regarded as key indicators of a company's performance and overall market perception [1]. One of the main concerns for investors is the fluctuation of stock prices [2], which are influenced by various factors, including national policy changes, domestic and global economic conditions, and international geopolitical events [3]. Due to their often nonlinear nature, stock price variations present considerable challenges for accurate prediction [2]. Consequently, stock price forecasting has become a central focus in economic research [4, 5]. Accurate and reliable predictions can significantly reduce investment risks by helping investors incorporate forecasts into their strategies to optimize returns.

One stock of particular relevance is PT Unilever Indonesia Tbk., a constituent of the $LQ45$ index, which reflects its liquidity and market significance. With a Return on Assets (ROA) of 47.4%, the company demonstrates strong performance [6], yet its stock price remains vulnerable to both internal and external shocks [7]. In addition to business fundamentals, external pressures such as global geopolitical issues have amplified volatility. Boycotts of Unilever products in response to its perceived support for Israel during humanitarian crises in Palestine have generated market uncertainty and contributed to fluctuations in stock prices [8]. Prior studies have provided empirical evidence that geopolitical risk significantly increases stock market volatility across both developed and emerging markets [9]. Such findings reinforce the view that even fundamentally strong companies are highly susceptible to geopolitical dynamics, thereby underscoring the need for reliable forecasting approaches to anticipate market fluctuations.

Given PT. Unilever Indonesia's stock price's sensitivity to both internal fundamentals and external geopolitical shocks, accurately capturing these fluctuations requires a model capable of handling time-varying volatility. Traditional models often fail to address heteroscedasticity and volatility clustering, which are commonly observed in financial time series [10]. Therefore, specialized models such as the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH) are employed, as they are designed to model conditional variance and improve forecasting accuracy for volatile stock prices [11, 12].

Empirical studies have shown that ARCH-GARCH models exhibit strong forecasting performance in Indonesian capital markets. In one study, the ARCH-GARCH (1,1) model applied to PT. Telekomunikasi Indonesia's stock data yielded AIC and BIC values of 11.441 and 11.586, respectively, confirming its suitability for capturing volatility dynamics [11]. However, despite their effectiveness, ARCH-GARCH models remain sensitive to residual noise and structural breaks, which can reduce forecasting accuracy over time. To enhance forecasting accuracy, the Kalman Filter can be integrated due to its ability to filter out noise, adapt to dynamic changes, and provide real-time estimations [13, 14]. Previous studies have shown that the Kalman Filter often outperforms traditional models such as ARIMA, ANN, and even hybrid models, particularly in contexts involving noisy or volatile data [15]. Therefore, combining ARCH-GARCH with the Kalman Filter offers a promising hybrid framework for forecasting the stock price of PT Unilever Indonesia, which exhibits moderate volatility influenced by both internal and external drivers [16]. This research utilizes daily closing stock price data of PT Unilever Indonesia as the primary dataset, covering the period from January 1, 2014, to December 31, 2024.

The objective of this study is to identify the most appropriate ARCH-GARCH model for forecasting the stock price of PT Unilever Indonesia and to assess the impact of integrating the Kalman Filter on forecasting performance. In line with this objective, the study addresses the following research questions: which ARCH-GARCH specification best captures the volatility of PT Unilever Indonesia's stock prices; does the incorporation of the Kalman Filter enhance forecasting accuracy compared to a conventional ARCH-GARCH model. The findings are expected to contribute to the development of time-series forecasting methodologies and to provide practical insights for stock price prediction in the consumer goods sector.

2 Research Method

The following Figure 1 is a flowchart of the research method. The research framework includes the following stages:

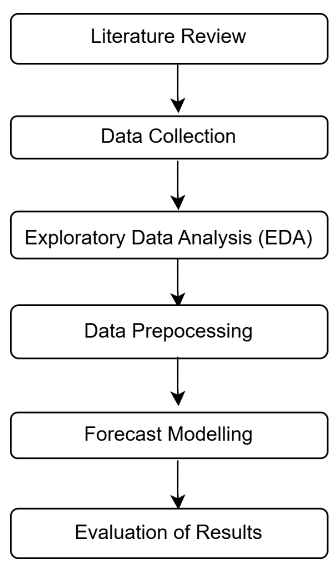


Figure 1: Research flowchart.

2.1 Literature Review

This study conducts a literature review on previous research concerning time series modeling and volatility forecasting to provide a robust theoretical framework for the analysis.

2.2 Data Collection

This study uses historical stock price data from Unilever Indonesia, obtained via the `yfinance` library in Python, which pulls data from Yahoo Finance. The dataset comprises

2,719 daily observations, including Open, High, Low, Close, Adjusted Close, and Volume. The selected period covers various market conditions, which are essential for accurate forecasting.

2.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) is conducted to understand the dataset's underlying characteristics. This process includes examining the data structure, generating descriptive statistics, and analyzing data distributions. During this stage, potential issues such as missing values or outliers can be identified before further processing.

2.4 Data Preprocessing

Data preprocessing was carried out to ensure the dataset was suitable for modeling. This stage included feature selection to retain the most relevant variables, namely the date and closing price, to reduce model complexity and improve predictive accuracy. To enhance data quality, the dataset was also examined for missing values and outliers. When present, missing values may be imputed, and extreme outliers may be removed. In addition, a Box-Cox transformation was applied to stabilize variance, and differencing was employed to resolve non-stationarity in the mean, thereby ensuring that the series met the assumptions required for model fitting.

2.5 Forecast Modeling

This study employs two forecasting approaches: ARCH-GARCH for modeling volatility and the Kalman Filter for smoothing and dynamic estimation.

2.5.1 ARCH-GARCH

The ARCH-GARCH (Autoregressive Conditional Heteroskedasticity-Generalized Autoregressive Conditional Heteroskedasticity) model is utilized to assess volatility through a structured sequence of procedures [17]. Initially, stationarity is evaluated using correlograms derived from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). When non-stationarity in variance is detected, a Box-Cox transformation is applied; for non-stationarity in the mean, differencing is employed. Once stationarity is achieved, an ARIMA model is fitted to the data. Subsequently, heteroscedasticity (ARCH effect) is tested using the Ljung-Box test on the squared residuals, along with the ARCH-LM test [18]. If significant ARCH effects are detected, the modeling proceeds by estimating various ARCH and GARCH variants.The general specification of the GARCH(p,q) model is as follows [19]:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_i \varepsilon_{t-i}^2 + \beta_j \sigma_{t-j}^2 \tag{1}$$

where σ_t^2 represents the conditional variance at time t, ε_{t-1}^2 denotes the squared residuals (past shocks), and σ_{t-j}^2 is the past conditional variance. After estimating several ARCH and GARCH model variants, the optimal model is selected based on the lowest Akaike Information Criterion (AIC) value. The AIC is calculated using the following formula [20]:

$$\text{AIC} = 2k - 2ln(L) \tag{2}$$

where k denotes the number of estimated parameters, L represents the value of the likelihood function, and n refers to the total number of observations in the sample. This approach ensures the selection of the most accurate model for forecasting stock price volatility.

2.5.2 Kalman Filter

The Kalman Filter is a recursive algorithm commonly used to estimate time-varying states in systems subject to noise [21]. Its implementation involves a sequence of steps, as illustrated in Figure 2.

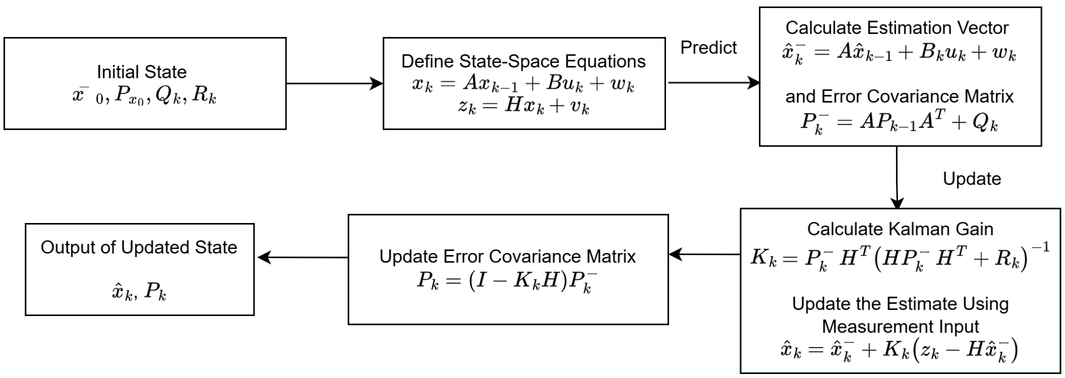


Figure 2: Kalman Filter.

The Kalman Filter algorithm operates through the following steps [22]: initializing the state estimate $\bar{x}_0$, the error covariance P_{x_0}, process noise Q_k, and measurement noise R_k; constructing the state-space model and measurement model; performing the prediction step by estimating $\hat{x}_k^-$ and P_k^-; executing the update step by computing the Kalman Gain K_k, and updating the estimates $\hat{x}_k$ and P_k. This iterative process continues until all data points are processed. The Kalman Filter is widely recognized as an effective algorithm for estimating time-varying variables in the presence of noise.

2.6 Evaluation of Results

Evaluation and analysis are performed by comparing the forecasting performance of the ARCH-GARCH model and the ARCH-GARCH model enhanced with the Kalman Filter using three evaluation metrics: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). MAPE quantifies the average percentage deviation between actual and forecasted values, thereby serving as an indicator of the model's relative accuracy in predicting stock prices, and is formulated as follows [23]:

$$\text{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{|Y_i - X_i|}{Y_i}\right) \times 100\%. \tag{3}$$

RMSE, which places greater weight on larger errors, assesses the model's ability to minimize substantial forecasting errors [24]. This aspect is particularly important in financial contexts, where large errors may lead to significant risks in decision-making, and is defined as [23]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2}. \tag{4}$$

Meanwhile, MAE measures the average magnitude of forecasting errors regardless of direction, thereby providing an intuitive and straightforward assessment of the model's overall reliability, and is expressed as follows [23]:

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i|. \tag{5}$$

In this formula, Y_i denotes the actual (observed) value, X_i represents the predicted (forecasted) value, and m indicates the total number of observations. Collectively, these three metrics provide a comprehensive evaluation of forecasting accuracy, directly aligned with the study's objective of examining whether integrating the Kalman Filter improves the predictive capability of ARCH-GARCH models for forecasting the stock price of PT Unilever Indonesia. Accordingly, lower metric values signify greater forecasting accuracy and enhanced model performance [24]. The resulting values are subsequently analyzed to assess and compare the forecasting effectiveness of each model.

3 Results

3.1 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to assess the data structure, analyze descriptive statistics, check for missing values, and identify potential outliers. The dataset consists of 2.719 rows and seven columns (Date, Open, High, Low, Close, Adjusted Close, and Volume) from January 1, 2014, to December 31, 2024. No missing values were detected, and thus, no imputation was necessary. The descriptive statistics for PT. Unilever Indonesia's stock price are presented in Table 1, providing further insights into the distribution of the observed variables.

Table 1: Descriptive statistics of PT Unilever Indonesia's stock price

Statistics	**Open**	**High**	**Low**	**Close**	**Adj Close**	**Volume**
Min	3290	3410	3280	3280	3071	0
1st Qu	5276	5360	5185	5256	4613	6588625
Median	7800	7890	7725	7795	6536	9906700
Mean	7241	7311	7160	7237	6203	13183527
3rd Qu	8900	8980	8810	8900	7496	15037125
Max	11235	11620	11180	11180	9414	250903800

As presented in Table 1, the stock prices of PT. Unilever Indonesia range from approximately 3,280 to over 11,000, with median values between 7,725 and 7,800. The Volume variable shows significant variation, ranging from 0 to over 250 million, with an average of around 13 million. The substantial interquartile range (IQR), particularly for stock prices, indicates notable volatility over the observed period.

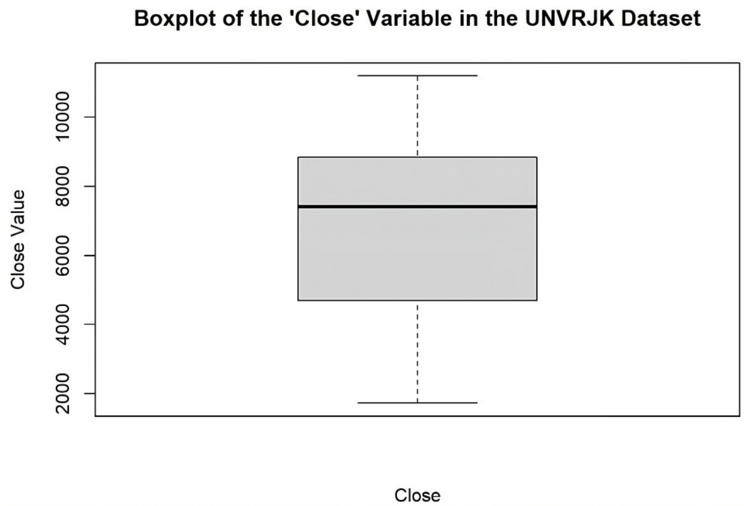


Figure 3: Boxplot of the close variable.

Based on Figure 3, the boxplot shows no extreme outliers. However, the relatively wide interquartile range (IQR) confirms significant fluctuations in stock prices, suggesting that the data is generally stable despite high variability.

3.2 Data Preprocessing

The dataset underwent preprocessing to ensure it was suitable for modeling. This process involved feature selection, selecting the Date and Close columns as the primary variables, and removing unused columns. The Date column records the timestamps of stock prices, while the Close column records the closing price, which is considered more stable and is commonly used for trend analysis and price forecasting.

A time series plot (Figure 4) was then employed to examine the price movement patterns of PT Unilever Indonesia's stock over 10 years. The analysis reveals substantial fluctuations in stock prices, indicating significant variability, which provides a foundation for modeling with the ARCH-GARCH approach to predict future stock price volatility.

3.3 Forecast Modeling

The modeling stage analyzes stock price volatility using the ARCH-GARCH model. The steps include stationarity testing, ARIMA model identification, heteroscedasticity detection, and the application and diagnostic testing of the ARCH-GARCH model. Once the best model is obtained, the Kalman Filter is applied to improve volatility estimation. Model evaluation is conducted by comparing performance based on Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Figure 4: Time series plot of the close variable.

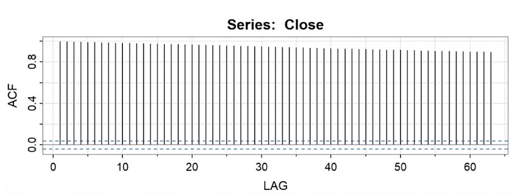
3.3.1 Stationarity Testing and Data Transformation

The ARCH-GARCH modeling process begins with stationarity testing to ensure the data meet the model's assumptions. The stationarity test is performed on both the variance and the mean. Table 2 displays the outcomes of the stationarity tests conducted on the stock price data.

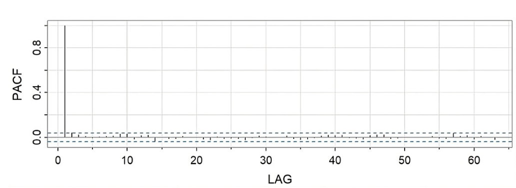
Table 2: Stationarity test results for stock price Data

Type of Stationarity	Test Method	Test Result	Decision
Variance	Box-Cox Transformation	$\lambda = 0.3854476$	Data is non-stationary in terms of variance, transformation is necessary
Mean	Augmented Dickey-Fuller (ADF)	$p - value = 0.6225 (> 0.05)$	Data is non-stationary in terms of mean, differencing is required

Following this, analyses using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were conducted to identify the appropriate order for the ARIMA model, as illustrated in Figure 5.



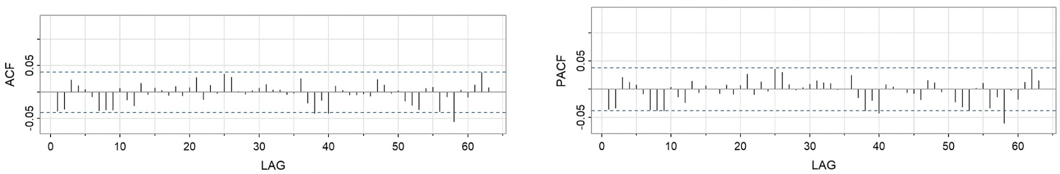
(a) ACF



(b) PACF

Figure 5: Plot of stock price data: (a) ACF and (b) PACF.

As shown in Figure 5(a) and Figure 5(b), the analysis revealed that the data are not stationary, prompting the application of logarithmic transformation and first differencing. After these transformations, the results of the ACF and PACF analyses are displayed in Figure 6(a) and Figure 6(b).



(a) ACF (b) PACF

Figure 6: Plot after log transformation and differencing (a) ACF (b) PACF.

Figure 6 displays the ACF and PACF after the transformations, showing minimal remaining autocorrelation, approximating white noise. Finally, after applying the logarithmic transformation and first differencing, the data were reassessed for stationarity. The results are shown in Table 3.

Table 3: Stationarity test results for stock price data

Type of Stationarity	**Test Method**	**Test Result**	**Decision**
Variance	Box-Cox Transformation	$\lambda = 1$	Data is stationary with respect to variance
Mean	Augmented Dickey-Fuller (ADF)	p-value $= 0.01 (< 0.05)$	Data is stationary with respect to mean

Upon confirming the data's stationarity, as outlined in Table 3, the next step is to select a suitable ARIMA model to capture the volatility of the stock price.

3.3.2 ARIMA Model Selection and Heteroscedasticity Identification

After confirming the data's stationarity, the next step was to estimate the ARIMA model. The appropriate model order was initially determined using the Extended Autocorrelation Function (EACF), which assists in identifying the optimal autoregressive (p) and moving average (q) components.

Figure 7 presents the results of the Extended Autocorrelation Function (EACF), which assists in identifying the optimal ARIMA model by highlighting the region where most entries become insignificant (denoted by "x"). Based on the EACF results, multiple ARIMA model configurations were assessed using the Akaike Information Criterion (AIC). Among them, the ARIMA (2,1,11) model was identified as the most appropriate, having yielded the lowest AIC value of $-13,888.77$. However, several alternative models also demonstrated comparable AIC values, including ARIMA (5,1,7) with an AIC of -13,887.60, ARIMA (2,1,3) with an AIC of $-13,886.83$, ARIMA (2,1,13) with an AIC of $-13,886.69$, and ARIMA (5,1,13) with an AIC of $-13,886.59$. Although these alternative models perform similarly, the ARIMA (2,1,11) model remains the preferred choice due to its slightly better fit under the AIC criterion.

```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x x o o o o o o x o o  o  x  o
1 x o o o o o o o x o o  o  x  o
2 x x o o o o o o x o o  o  x  o
3 x x x o o o o o o o o  o  x  o
4 x x o o o o o o o o o  o  o  o
5 x x x o o o o o o o o  o  o  o
6 x x x o o x o o o o o  o  o  o
7 x x o o o x x o o o o  o  o  o
```

Figure 7: Presents the EACF results.

Following the preliminary ARIMA model selection, heteroscedasticity in the residuals was assessed. Normality was assessed using a QQ-Plot, and the presence of autocorrelation in the residuals (white noise assumption) was examined using the Ljung-Box test. The hypotheses for the Ljung-Box test are [25]:

$H_0 : \rho_k = 0$, The residuals do not exhibit autocorrelation and can be considered white noise. $H_1 : \rho_k \neq 0$, The residuals exhibit autocorrelation and cannot be considered white noise.

Table 4: Model comparison based on residual diagnostics and AIC values

Model	Normality Test	White Noise Test	AIC
ARIMA (2,1,11)	Not Normal	No White Noise	-13.888,77
ARIMA (5,1,7)	Not Normal	No White Noise	-13.887,60
ARIMA (2,1,3)	Not Normal	White Noise	-13.886,83
ARIMA (2,1,13)	Not Normal	No White Noise	-13.886,69
ARIMA (5,1,13)	Not Normal	No White Noise	-13.886,59

Based on the results in Table 4, all models exhibited residuals that did not follow a normal distribution. However, only the ARIMA (2,1,3) model satisfied the white noise assumption, indicating that the residuals showed no significant autocorrelation. Therefore, parameter estimation was conducted for the ARIMA (2,1,3) model, with the results presented in Table 5.

The ARIMA (Autoregressive Integrated Moving Average) model is a widely used method for time series forecasting that integrates three components: autoregression (AR), differencing (I), and moving average (MA). Its general form is expressed as follows [26]:

$$(1-B)^d X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}. \quad (6)$$

where B is the backshift operator ($BX_t = X_{t-1}$), d is the differencing order, ϕ_1 and θ_j are the AR and MA coefficients, and e_t is the white noise error. Referring to Equation

Table 5: Parameter estimation for the ARIMA (2,1,3) model

Model	Parameter	Estimate	Standard Error	AIC
ARIMA (2,1,3)	ϕ_1	-1.5319	0.0038	$-13,886.83$
	ϕ_2	-0.9970	0.0056	
	θ_1	0.5315	0.0051	
	θ_2	-0.5353	0.0059	
	θ_3	-0.9907	0.0093	

(6) and considering $p = 2$,$d = 1$,$q = 3$, the expanded form of the ARIMA (2,1,3) model is: This final equation represents the fitted ARIMA (2,1,3) model for the log-transformed and differenced stock price data.

$$\mathrm{X_t} = -0.5319X_{t-1}+0.5349X_{t-2}+0.9970X_{t-3}-0.5315e_{t-1}+0.5353e_{t-2}+0.9907e_{t-3}+e_t \quad (7)$$

To verify the existence of heteroskedasticity within the residuals of the ARIMA (2,1,3) model, a Lagrange Multiplier (LM) test was conducted. The hypotheses for the LM test are [27]: $H_0 : \alpha_0 = \alpha_1 = \cdots = \alpha_p = 0$, indicating that the model residuals do not exhibit ARCH effects. H_1 : At least one $\alpha_i \neq 0$, indicating the presence of ARCH effects in the model residuals, where $(i = 1, 2, 3, ..., p)$

Table 6: Parameter Estimation for the ARIMA (2,1,3) Model

LM Test	
Chi-squared	275.96
df	10
$\mathrm{p-value}$	$2.2e-16$

Table 6 presents the LM test results, with a $\mathrm{p-value}$ of 2.2×10^{-16}, which is below the 0.05 significance level. These results indicate rejection of the null hypothesis, confirming the presence of ARCH effects. Thus, the ARIMA (2,1,3) model alone is insufficient to capture volatility, and ARCH-GARCH models are recommended.

3.3.3 ARCH-GARCH Modelling

Following the detection of ARCH effects in the ARIMA (2,1,3) model residuals, further analysis was conducted using ARCH-GARCH modeling techniques. Before estimating the model, the dataset was split into two subsets: a training set comprising 80% of the observations (2,174 data points) and a test set comprising the remaining 20% (544 data points). This proportion was chosen to ensure the model's estimation accuracy while maintaining a sufficient sample size for performance evaluation.

Subsequently, a comprehensive exploration of various specifications of the GARCH and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) models was conducted. The GJR-GARCH model extends the standard GARCH framework by incorporating asymmetries in shock responses, whereby negative shocks (bad news) exert a different influence on volatility compared to positive shocks (good news). This feature makes GJR-GARCH particularly suitable for modeling financial time series that exhibit leverage effects. Multiple combinations of lag orders (p, q) were tested under three different error distribution assumptions: normal, Student's t (std), and skewed Student's t (sstd).

The performance of the various GARCH and GJR-GARCH specifications was systematically evaluated to identify the most appropriate model for capturing stock price volatility. The comparative results, summarized in Table 7, illustrate model variations across different lag structures and error distributions, offering a concise overview of model performance before the detailed examination of estimated parameters. Model selection was guided by the Akaike Information Criterion (AIC), which quantifies the information lost when approximating reality [28]. A lower AIC value indicates a better fit and improved predictive capability [29]. Accordingly, the optimal model was identified as the one with the lowest AIC value (Table 7).

Table 7: Comparative evaluation of GARCH and GJR-GARCH models

Model	**Error Distribution**	**AIC**
GJR-GARCH (2,1)	sstd	-5.479.345
GJR-GARCH (1,3)	sstd	-5.478.636
GJR-GARCH (3,1)	sstd	-5.477.729
GARCH (1,2)	sstd	-5.476.981
GARCH (2,2)	sstd	-5.476.061

As shown in Table 7, the comparison across models highlights substantial differences in fit quality depending on lag structure and error distribution. To ensure the robustness of the selected model, the estimated parameters of the optimal ARCH-GARCH and GJR-GARCH models were examined for statistical significance (Table 8). Each parameter is presented along with its standard error, $\mathrm{z-value}$, and $\mathrm{p-value}$, where the z-value indicates how many standard deviations the estimate is from zero, and the $\mathrm{p-value}$ represents the probability of observing such a value under the null hypothesis that the parameter equals zero [30]. Parameters with $\mathrm{p-value}$ below the significance threshold ($\alpha = 0.05$) are considered statistically significant, confirming their meaningful contribution to explaining volatility dynamics and ensuring that the model is both well-fitted and stable.

Based on the results presented in Table 7 and Table 8, the GJR-GARCH (2,1) model with skewed Student's t-distribution (sstd) yielded the lowest AIC value of $-5.479.345$, indicating the best in-sample performance among all evaluated models. However, parameter estimation results revealed instability, as the model produced a NaN (Not a Number) value for the ω parameter, and several other parameters were statistically insignificant. These issues suggest a lack of model robustness and potential overfitting.

In contrast, the GARCH (1,2)-sstd model, although slightly less optimal in terms of AIC (-5.476.981) yielded more stable parameter estimates, with most parameters being statistically significant. While the ω parameter was not significant, it retained a reasonably estimated value, indicating acceptable behavior. Considering the trade-off between model fit (as measured by AIC) and parameter stability, the GARCH (1,2) model with a skewed Student's t-distribution was identified as the most suitable model for capturing the volatility behavior of PT. Unilever Indonesia's stock price.

Referring to the general form of the GARCH model as presented in Equation (1), and by substituting the estimated parameters from Table 9, the final fitted GARCH (1,2) model

Table 8: Significance test results of the ARCH-GARCH model

Model	Parameter	Estimate	Std. Error	z − value	p − value	Significance Test
GJR-GARCH (1,3)	ω	0.000015	0.000007	1.984	$4.72e-02$	Significance
	α_1	0.158033	0.040986	3.856	$1.15e-04$	Significance
	β_1	0.200680	0.126664	1.584	$1.13e-01$	Not Significance
	β_2	0.270260	0.276275	0.978	$3.28e-01$	Not Significance
	β_3	0.296123	0.237474	1.247	$2.12e-01$	Not Significance
	γ_1	0.115183	0.053618	2.148	$3.17e-02$	Significance
GJR-GARCH (2,1)	ω	0.000007	NaN	NaN	NaN	NA
	α_1	0.082637	0.0327	2.524	$1.16e-02$	Significance
	α_2	0.000000	0.0396	0.000	$1.00e+00$	Not Significance
	β_1	0.888597	0.0093	95.501	$0.00e+00$	Significance
	γ_1	0.268141	0.0820	3.269	$1.08e-03$	Significance
	γ_2	-0.234343	0.0768	-3.050	$2.29e-03$	Significance
GJR-GARCH(3,1)	ω	0.000008	NaN	NaN	NaN	NA
	α_1	0.083685	0.0323	2.584	$9.75e-03$	Significance
	α_2	0.000000	0.0508	0.000	$1.00e+00$	Not Significance
	α_3	0.000000	0.0372	0.000	$1.00e+00$	Not Significance
	β_1	0.885931	0.0112	78.935	$0.00e+00$	Significance
	γ_1	0.269291	0.0818	3.290	$1.00e-03$	Significance
	γ_2	-0.263804	0.0916	-2.877	$4.01e-03$	Significance
	γ_3	0.031650	0.0539	0.586	$5.58e-01$	Not Significance
GARCH(1,2)	ω	0.000014	0.000014	0.976	$3.29e-01$	Not Significant
	α_1	0.184064	0.082405	2.234	$2.55e-02$	Significant
	β_1	0.277234	0.135223	2.050	$4.03e-0e$	Significant
	β_2	0.517518	0.155004	3.339	$8.42e-04$	Significant
GARCH(2,2)	ω	0.000014	NaN	NaN	NaN	NA
	α_1	0.184054	0.042584	4.322	$1.55e-05$	Significant
	α_2	0.000000	NaN	NaN	NaN	NA
	β_1	0.277204	NaN	NaN	NaN	NA
	β_2	0.517562	NaN	NaN	NaN	NA

Table 9: Parameter estimation for the GARCH (1,2)-sstd

Model	Parameter	Estimate	Standard Error	AIC
GARCH (1,2)-sstd	ω	0.000014	0.000014	-5.476.981
	α_1	0.184064	0.082405	
	β_1	0.277234	0.135223	
	β_2	0.517518	0.155004	

can be expressed as follows:

$$\sigma_t^2 = 0.000014 + 0.184064\varepsilon_{t-1}^2 + 0.277234\sigma_{t-1}^2 + 0.517518\sigma_{t-2}^2. \quad (8)$$

This model was subsequently used to forecast future stock prices. A comparison between the actual and predicted prices using the GARCH (1,2)-sstd model is presented in Figure 8.

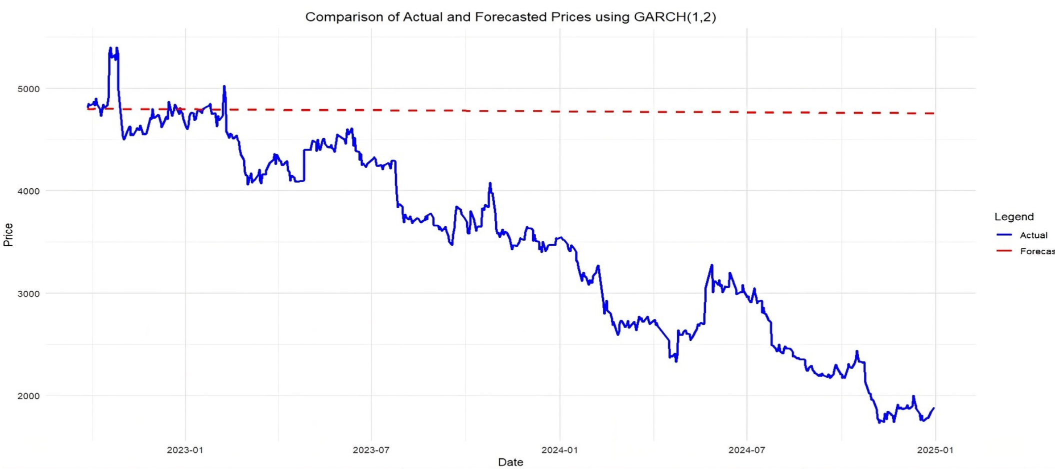


Figure 8: Comparison of actual prices and GJR-GARCH (2,1) predictions.

As shown in Figure 8, the forecasted values from the GARCH (1,2)-sstd model tend to remain relatively stable and fail to capture the sharp fluctuations in actual stock prices. The gap between the actual and predicted values widens over time, indicating that the model lacks responsiveness to downward trends and periods of high volatility. The model produced a MAPE of 49.47%, with RMSE and MAE values of 1,593.04 and 1,299.52, respectively. When expressed as percentages relative to the actual stock prices, the RMSE and MAE were 45.56% and 37.16%, respectively, indicating relatively high prediction errors both in absolute and relative terms.

3.3.4 ARCH-GARCH with the Application of the Kalman Filter

Following the use of the GARCH(1,2)-sstd model, which yielded a MAPE of 49.47% and demonstrated limited responsiveness to price fluctuations, further refinement was undertaken by applying the Kalman Filter. This method aims to filter out noise and produce more optimal volatility estimates by dynamically updating predictions. The GARCH(1,2)-sstd model was reformulated into a state-space representation without an external control matrix, since no control variables were included. The state equation is given as:

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{w}_k \tag{9}$$

This can be written in matrix form as:

$$\begin{bmatrix} \sigma_t^2 \\ \sigma_{t-1}^2 \\ \varepsilon_t^2 \end{bmatrix} = \begin{bmatrix} \beta_1 & \beta_2 & \alpha_1 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \sigma_t^2 \\ \sigma_{t-1}^2 \\ \varepsilon_t^2 \end{bmatrix}_{k-1} + w_k \tag{10}$$

The measurement equation is defined as:

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \tag{11}$$

which can be written as:

$$z_k = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_t^2 \\ \sigma_{t-1}^2 \\ \varepsilon_t^2 \end{bmatrix} + v_k \tag{12}$$

Once the system and measurement models were defined, the next step was to initialize the parameters. The initial values were derived from the first forecast generated by the GARCH (1,2)-sstd model. The process noise variance $\bar{Q}$ was set to 10^{-1}, while the measurement noise variance was calculated from the test data variance. The initial state $\hat{x}_0$ and the initial covariance matrix P_0 were defined as follows:

$$\hat{x}_0 = \begin{bmatrix} 0.0007668235 \\ -0.0004929003 \\ 0.000004331253 \end{bmatrix}, \quad P_0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Q_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{13}$$

The prediction step involved estimating the state vector:

$$\hat{\mathbf{x}}_k^- = \mathbf{A}\hat{\mathbf{x}}_{k-1} + \mathbf{w}_k \tag{14}$$

And the prediction covariance:

$$P_k^- = \mathbf{A}P_{k-1}\mathbf{A}^T + Q_k \tag{15}$$

Here, the transition matrix **A** was derived from the estimated parameters of the GARCH (1,2)-sstd model. The correction step involved calculating the Kalman gain [22]:

$$K_k = P_k^- \mathbf{H}^T \left(\mathbf{H}P_k^- \mathbf{H}^T + R_k \right)^{-1} \tag{16}$$

And updating the state estimate:

$$\hat{x}_k = \hat{x}_k^- + K_k \left(z_k - \mathbf{H}\hat{x}_k^- \right) \tag{17}$$

As well as updating the error covariance matrix:

$$P_k = (I - K_k\mathbf{H})P_k^- \tag{18}$$

In this study, the observation matrix H was defined as $\begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$, indicating that only the squared residuals ϵ_t^2 were observed. After filtering, the forecasted stock prices were transformed back to their original scale using an exponential transformation. The Kalman Filter estimation was implemented in R Studio over 544 iterations, corresponding to the number of test observations. The results demonstrated a significant improvement in forecasting accuracy, with the MAPE reduced to 6.05%, RMSE to 210.22, and MAE to 175.64. In relative terms, the RMSE and MAE accounted for 6.01% and 5.02% of the actual stock prices, respectively, indicating high predictive performance.

As shown in Figure 9, the GARCH (1,2)-sstd model integrated with the Kalman Filter provides forecasts that better track actual stock price movements, especially during sharp fluctuations. In contrast, the standalone GARCH model tends to produce overly smoothed forecasts. The red line (Kalman-enhanced) aligns more closely with the blue line (actual prices) than the green dashed line (standard GARCH), highlighting the Kalman approach's improved responsiveness.

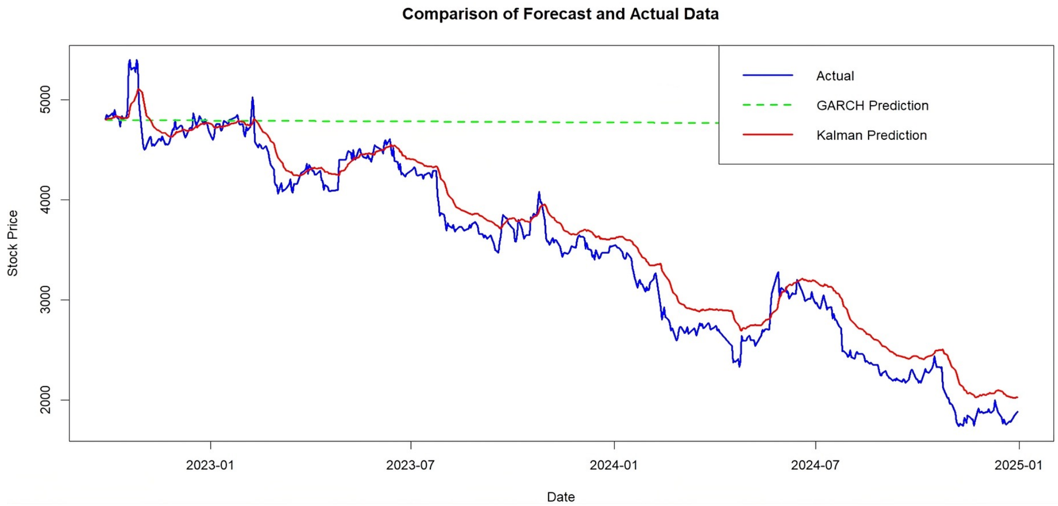


Figure 9: Comparison of actual prices and forecasts from GARCH (1,2) and GARCH (1,2) with Kalman Filter.

3.4 Evaluation Model

After applying the GARCH(1,2)-sstd model combined with the Kalman Filter to forecast the stock price of PT. Unilever Indonesia, the predicted values were compared with the actual prices, as shown in Figure 8. The results indicate that the model integrated with the Kalman Filter produced forecasts that were more accurate and closer to actual stock prices, in contrast to the standalone GARCH(1,2)-sstd model, which tended to generate stable predictions that were less responsive to price fluctuations.

Table 10: Forecasting error evaluation

Model	MAPE (%)	RMSE (%)	MAE (%)
GARCH (1,2)	49.47%	45.56%	37.16%
GARCH (1,2) with Kalman Filter	6.03%	6.01%	5.02%

The error evaluation results in Table 10 further support the superiority of the Kalman-enhanced model. The MAPE decreased significantly from 49.47% in the standalone GARCH(1,2)-sstd model to 6.05% with the Kalman Filter. Similarly, the RMSE dropped from 45.56% to 6.01%, and the MAE decreased from 37.16% to 5.02%, indicating substantial improvements in both absolute and relative forecasting accuracy.

These findings hold important implications for the consumer goods sector, particularly for companies such as PT. Unilever Indonesia. The substantial reduction in forecasting errors suggests that integrating the Kalman Filter with GARCH models yields more reliable volatility predictions, enabling better risk management and strategic decision-making. For investors, the model's improved responsiveness enhances their ability to anticipate market fluctuations and adjust portfolios accordingly. Meanwhile, for company stakeholders, accurate forecasts support financial planning, hedging strategies, and the maintenance of investor confidence in a sector that is highly sensitive to consumer demand and market dynamics.

4 Discussion

The findings of this study demonstrate that the GARCH(1,2) model with a skewed Student's t-distribution (sstd) effectively captures volatility in PT. Unilever Indonesia's stock prices, aligning with previous research that emphasizes the usefulness of ARCH-GARCH models for modeling financial time series with heteroscedasticity [12, 31]. However, while the model exhibited relatively low AIC values and stable parameters, its forecasting performance remained limited when facing sharp price fluctuations. This is reflected in the model's high error rates: MAPE of 49.47%, RMSE of 45.56%, and MAE of 37.16%.

By integrating the Kalman Filter into the GARCH framework, a notable improvement in forecasting accuracy was achieved. The filter's ability to dynamically update predictions and mitigate observational noise made the model more responsive to price volatility, resulting in a substantial decrease in prediction error. The MAPE dropped significantly to 6.04%, with corresponding reductions in RMSE and MAE to 6.01% and 5.02%, respectively. These improvements support the findings of [13], who also reported enhanced accuracy in financial forecasts using Kalman-based approaches. Similarly, [32] confirmed the effectiveness of the Kalman Filter in improving forecasting performance. This study strengthens that evidence by showing that its integration into the GARCH framework enhances forecasting accuracy in volatile markets.

The hybrid GARCH-Kalman model offers both theoretical and practical advantages. By combining static and dynamic estimation techniques, it enhances volatility modeling and improves forecast precision, thereby assisting investors and analysts in making informed decisions under volatile conditions. In the consumer goods sector, which is generally stable yet vulnerable to socio-political and economic shocks, the model provides an early warning system that supports risk management and portfolio strategies. Compared to studies on high-volatility sectors such as banking or energy, these findings demonstrate the model's broader applicability to industries that balance resilience with external vulnerabilities.

Despite these contributions, the study has several limitations. The analysis relies solely on historical price data and excludes exogenous factors such as exchange rates, inflation, and market sentiment, all of which may influence stock price dynamics. Furthermore, the scope is limited to a single company, restricting the generalizability of the findings. Future research could extend the model by integrating macroeconomic indicators, sentiment analysis, and multi-firm datasets to strengthen its robustness and practical relevance.

5 Conclusion

Based on the analysis and evaluation, the most appropriate model for capturing the volatility of PT. Unilever Indonesia's stock price is the GARCH(1,2) model with a skewed Student's t-distribution (sstd). This model was selected due to its relatively low AIC value of -5.476981 and the stability of its parameter estimates. The final form of the model is expressed as $\sigma_t^2 = 0.000014 + 0.184064\varepsilon_{t-1}^2 + 0.277234\sigma_{t-1}^2 + 0.517518\sigma_{t-2}^2$. When applied independently, the GARCH(1,2)-sstd model yielded a MAPE of 49.47%, a RMSE of 45.56%, and a MAE of 37.16%. These values indicate that the model has moderate forecasting ability, but with limited responsiveness to sudden changes or extreme volatility in stock prices.

To address this limitation, the Kalman Filter was integrated with the model. The application of the Kalman Filter significantly enhanced forecasting performance, reducing the MAPE to 6.04%, the RMSE to 6.01%, and the MAE to 5.02%. This improvement demonstrates the Kalman Filter's effectiveness in dynamically adjusting predictions, filtering out noise, and improving the model's adaptability to data fluctuations.

This study confirms that the hybrid GARCH-Kalman model improves stock price forecasting accuracy, offering concrete benefits for investors and companies. Investors can use the model to dynamically adjust their portfolio allocation, optimize hedging strategies, and minimize potential losses. Companies can leverage forecasts to plan cash flow, time stock buybacks or issuances, and make pricing decisions to enhance financial stability. By providing more reliable predictions, this model supports informed decision-making and risk management in real financial settings.

Future research should integrate macroeconomic indicators and alternative data sources such as sentiment from financial news and social media. The adoption of advanced approaches, including machine learning and nonlinear models, is also recommended to reduce prediction errors and create a more comprehensive forecasting framework. These enhancements aim to improve predictive accuracy and strengthen the practical relevance of forecasting models in dynamic market conditions.

References

[1] F. Saputra, "Analysis effect return on assets (roa), return on equity (roe) and price earning ratio (per) on stock prices of coal companies in the indonesia stock exchange (idx) period 2018-2021," *DIJEFA: Dinamika International Journal of Economics, Finance, and Accounting*, vol. 3, no. 1, pp. 82–94, 2022.

[2] W. Lu, J. Li, J. Wang, and L. Qin, "A cnn-bilstm-am method for stock price prediction," *Neural Computing and Applications*, vol. 33, no. 10, pp. 4741–4753, 2021.

[3] D. R. Chauhan, D. V. Gupta, and D. R. Shridh, "Analysis of stock market fluctuations and global economic conditions- a review," *Business, Management and Economics Engineering*, vol. 21, no. 01, 2023.

[4] C. Xiao, W. Xia, and J. Jiang, "Stock price forecast based on combined model of arima-ls-svm," *Neural Computing and Applications*, vol. 32, no. 10, pp. 5379–5388, 2020.

[5] P. Yu and X. Yan, "Stock price prediction based on deep neural networks," *Neural Computing and Applications*, vol. 32, no. 6, pp. 1609–1628, 2020.

[6] I. Ina, A. D. Octavia, T. Fauziah, and D. Haryadi, "Financial statement analysis ... pt unilever indonesia tbk ... 2018–2022 ... current ratio, debt equity ratio, and return on asset," *International Journal of Applied Finance and Business Studies*, vol. 11, no. 4, pp. 755–761, 2024.

[7] A. Sulaiman and L. Herlina, "Analysis of the effect of financial ratio on share price at pt unilever indonesia tbk period 2010-2021," *Journal of Business Management Indonesia*, vol. 2, no. 01, pp. 29–39, 2023.

[8] S. Azzahra, R. Ristati, M. Marzuki, and G. Syamni, "Jakarta islamic index stock market reaction to turmoil israel and palestine war," *Journal of Accounting Research, Utilities, and Financial Digital Assets*, vol. 3, no. 1, pp. 218–226, 2023.

[9] Y. Zhang, J. He, M. He, and S. Li, "Geopolitical risk and stock market volatility: A global perspective," *Finance Research Letters*, vol. 53, p. 103620, 2023.

[10] F. Setoudehtazangi, *Robust Mixture Models for Modeling and Clustering Complex Time Series Data*. PhD thesis, Università degli Studi di Padova, Padova, Italy, 2023.

[11] W. Alwi, A. P. S, and I. Syata, "Forcasting stock price pt. indonesian telecomunication with arch-garch model," *J. Varian*, vol. 5, no. 2, pp. 125–136, 2022.

[12] E. Coker-Farrell, Z. A. Imran, C. Spulbar, A. Ejaz, R. Birau, and R. C. Criveanu, "Forecasting the conditional heteroscedasticity of stock returns using asymmetric models ... eastern european countries," *Industria Textila*, vol. 72, no. 3, pp. 324–330, 2021.

[13] N. Deepika and M. N. Bhat, "An efficient stock market prediction method based on kalman filter," *Journal of The Institution of Engineers (India): Series B*, vol. 102, no. 4, pp. 629–644, 2021.

[14] M. Impraimakisa and A. W. Smyth, "A new residual-based kalman filter ... estimation using limited output information," *Mechanical Systems and Signal Processing*, vol. 178, 2022.

[15] A. T. Biva, S. A. Khan, and S. Hossain, "A comparative study of arima, artificial neural networks, and kalman filter models for dhaka stock exchange forecasting," *GANIT: Journal of Bangladesh Mathematical Society*, vol. 44, pp. 29–58, 2024.

[16] U. Juanda, Y. Sudaryo, M. M. Ali, G. D. Ismail, D. Febriyanti, and R. Muttaqin, "The influence of return on assets (roa), current ratio (cr), and debt-to-equity ratio (der) on stock prices at pt. unilever indonesia tbk period 2014-2023," *Jurnal Sosial Sains*, vol. 5, no. 2, pp. 132–145, 2025.

[17] J. A. Alzyadat, A. A. Abuhommous, and H. Alqaralleh, "Testing the conditional volatility of saudi arabia stock market: Garch approach," *Academy of Accounting and Financial Studies Journal*, vol. 25, no. 2, pp. 1–9, 2021.

[18] B. Dinga, J. H. Claver, K. K. Cletus, and S. F. Che, "Modeling and predicting exchange rate volatility: ... garch, egarch, and gjr-garch models," *Journal of the Cameroon Academy of Sciences*, vol. 19, no. 2, pp. 155–178, 2023.

[19] Z. Qian and X. Xu, "An option valuation formula for stochastic volatility driven by garch processes," *Journal of Mathematical Finance*, vol. 13, no. 02, pp. 221–247, 2023.

[20] Y. Zhang and G. Meng, "Simulation of an adaptive model based on aic and bic arima predictions," *Journal of Physics: Conference Series*, vol. 2449, no. 1, 2023.

[21] C. Busu and M. Busu, "An application of the kalman filter recursive algorithm to estimate the gaussian errors," *Symmetry*, vol. 13, no. 2, pp. 1–10, 2021.

[22] D. Gurin, V. Yevsieiev, A. Abu-Jassar, and S. Maksymova, "Using the kalman filter ... collaborative robot working area," *Multidisciplinary Journal of Science and Technology*, vol. 4, no. 8, pp. 66–75, 2024.

[23] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination r-squared is more informative ...," *PeerJ Computer Science*, vol. 7, pp. 1–24, 2021.

[24] Z. Luo, W. Guo, Q. Liu, and Z. Zhang, "A hybrid model for financial time-series forecasting based on mixed methodologies," *Expert Systems*, vol. 38, no. 2, pp. 1–16, 2021.

[25] L. S. Bjerkander, J. Dovern, and H. Manner, "Testing with vectors of statistics: Revisiting combined hypothesis tests," *CESifo Working Paper*, 2024.

[26] C. Huang and A. Petukhina, "Arma and arima modeling and forecasting," in *Applied Time Series Analysis and Forecasting with Python*, Springer, 2022.

[27] S. Kot and S. Ojinji, "Environmental sustainability and freight transport performance in the eu – arch model analysis," *Promet - Traffic and Transportation*, vol. 35, no. 5, pp. 621–634, 2023.

[28] M. Sarstedt and N. P. Danks, "Prediction in hrm research – a gap between rhetoric and reality," *Human Resource Management Journal*, vol. 32, no. 2, pp. 485–513, 2022.

[29] C. E. Clark *et al.*, "Higher arm versus lower arm systolic blood pressure ... interpress-ipd," *Hypertension*, vol. 79, no. 10, pp. 2328–2335, 2022.

[30] H. Shi and G. Yin, "Reconnecting p-value and posterior probability under one- and two-sided tests," *The American Statistician*, vol. 75, no. 3, pp. 265–275, 2021.

[31] A. Ejaz, P. Polak, and Z. A. Imran, "An investigation into share prices' conditional heteroscedasticity ... south africa, nigeria, and egypt," *Management*, vol. 26, no. 1, pp. 189–200, 2021.

[32] G. Patowari and R. Dey, "Stock market risk prediction of indian stocks using kalman filter: Towards automation of finance industry," in *2021 International Symposium on Asian Control Association Intelligent Robotics and Industrial Automation (IRIA)*, pp. 149–153, 2021.