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Modeling the Volatility-Return Relationship in the Indonesian Stock Market using the GARCH-M Framework

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ABSTRACT

The LQ45 Index was observed to be in the red zone, with a decline of 9.64% year-to-date (YTD), reaching the level of 877.02. The LQ45 Index became increasingly weakened following the announcement of Donald Trump's victory in the U.S. presidential election, which impacted the Indonesian capital market. It was recorded that the LQ45 Index fell by 5.3% during the final trading month of 2024. Nevertheless, there remains a potential for strengthening the stock prices of LQ45 constituent issuers in the remainder of this year, particularly in December 2024. One of the stocks recommended by IDX is PT Indofood CBP Sukses Makmur Tbk., which has also been one of the most liquid companies according to IDX throughout 2024. The return volatility of stocks in emerging markets is generally much higher than that of developed markets. High volatility reflects a higher level of risk faced by investors, as it indicates significant fluctuations in stock price movements. Therefore, equity investments in Indonesia carry a potentially high level of risk. A common characteristic of financial time series data, particularly return data, is that the probability distribution of returns exhibits fat tails and volatility clustering, often referred to as heteroscedasticity. Time series models that can be used to model these conditions include ARCH and GARCH models. One variation of the ARCH/GARCH models is the Generalized Autoregressive Conditional Heteroscedasticity in Mean (GARCH-M) model, which incorporates the effect of volatility into the mean equation. The purpose of this study is to predict volatility using the GARCH-M model in the analysis of daily closing price return data of PT Indofood CBP Sukses Makmur Tbk. The best model used for volatility forecasting is ARIMA(2,0,1) GARCH(1,1)-M.

KEYWORDS: Indonesian Stock Market, Stock Price Fluctuations, Risk, Heteroscedasticity

I. INTRODUCTION

The Indonesian capital market, as one of the emerging markets, has distinct characteristics compared to developed markets. One of its prominent features is high volatility, which indicates a higher level of uncertainty and risk faced by investors [1]. Volatility reflects fluctuations in stock prices over time, which directly impacts the potential gains or losses in stock investments. During periods of high volatility, investors are exposed to greater risks as stock prices tend to experience larger and more frequent changes.

Throughout 2024, the LQ45 Index, which consists of 45 stocks with the largest market capitalization and highest liquidity on the Indonesia Stock Exchange (IDX), recorded a significant decline. As of the end of the year, the LQ45 Index had dropped by 9.64% year-to-date (ytd), reaching the level of 877.02 [2]. This downturn was exacerbated by the global market's reaction to the announcement of Donald Trump's victory in the 2024 U.S. Presidential Election, which triggered market uncertainty and capital outflows from emerging markets such as Indonesia [3]. As a result, the LQ45 Index experienced an additional 5.3% decrease during the final trading month of 2024.

Despite these unfavorable conditions, there remains an opportunity for price recovery among the constituent stocks of the LQ45 Index. One of the stocks recommended by the IDX for its strong fundamentals and high liquidity is PT Indofood CBP Sukses Makmur Tbk. (ICBP). ICBP has been recognized as one of the most liquid stocks on the IDX throughout 2024 [3]. This makes ICBP a relevant subject for further analysis, particularly in terms of return volatility and risk assessment. Understanding the volatility of ICBP's stock returns is crucial for investors seeking to make informed decisions amidst uncertain market conditions.

The concept of volatility plays a vital role in modern financial theory and practice. Volatility is often used as a measure of market risk [4], and its accurate estimation is essential for asset pricing, risk management, and portfolio allocation [5]. In emerging markets such as Indonesia, stock return volatility tends to exhibit unique patterns, including volatility clustering—a phenomenon where periods of high volatility are followed by similar periods, and low volatility periods are followed by low volatility [6, 7]. Additionally, financial time series data, particularly stock returns, frequently display fat tails in their probability distributions. This indicates a higher likelihood of extreme price movements compared to what is predicted by a normal distribution [8].

Given these empirical characteristics, traditional time series models such as Autoregressive Integrated Moving Average (ARIMA) are insufficient for modeling financial time series data with conditional heteroscedasticity [9]. To address this limitation, Engle [4] introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which explicitly models time-varying volatility. Bollerslev [7] later generalized this model into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which has become widely adopted in volatility modeling due to its flexibility and accuracy.

A further development of the GARCH model is the GARCH-in-Mean (GARCH-M) model proposed by Engle, Lilien, and Robins [10]. The GARCH-M model allows the conditional variance (volatility) to directly affect the conditional mean of stock returns. This implies that investors demand higher returns as compensation for taking on higher risk, aligning with modern portfolio theory. The incorporation of risk into the return equation makes the GARCH-M model particularly relevant for studying the risk-return tradeoff in financial markets [10].

The Indonesian stock market, characterized by high volatility and sensitivity to both domestic and global economic events, presents a compelling case for the application of the GARCH-M model. PT Indofood CBP Sukses Makmur Tbk. (ICBP), as a leading consumer goods company with strong market presence, offers an ideal case study for analyzing stock return volatility using this model. By modeling ICBP's daily stock returns with a GARCH-M approach, it is possible to gain insights into the volatility-return relationship and assess the compensation investors require for bearing risk. some empirical studies showed that the GARCH-M and GJR GARCH models work well, e.g., in [11–15].

The objective of this study is to predict the volatility of daily stock returns of PT Indofood CBP Sukses Makmur Tbk. using the GARCH-M model. The empirical analysis conducted in this study identifies the ARIMA(2,0,1)-GARCH(1,1)-M model as the best-fit model for forecasting volatility in ICBP's stock returns throughout 2024. The results of this analysis are expected to provide valuable information for investors, portfolio managers, and policymakers in understanding the behavior of stock returns and the associated risks in the Indonesian capital market.

Furthermore, the findings contribute to the existing body of literature on volatility modeling in emerging markets and highlight the importance of adopting appropriate econometric models, such as GARCH-M, for more accurate risk measurement and investment decision-making [16, 17]. Accurate volatility forecasts are essential for optimizing investment strategies, determining appropriate risk premiums, and designing effective hedging techniques [18].

In conclusion, the volatility of stock returns in emerging markets, including Indonesia, remains a critical area of research in financial economics. The application of advanced time series models, such as the GARCH-M framework, provides a comprehensive approach to understanding and managing market risks. As the global investment landscape continues to evolve, incorporating volatility modeling into investment practices is crucial for achieving long-term financial stability and sustainable portfolio performance.

II. THEORETICAL FRAMEWORK

2.1. ARCH and GARCH Model

In general, time series data modeling is expected to fulfill the assumption of constant variance (homoscedasticity). However, financial sector time series data often exhibit very high volatility. This is indicated by the presence of non-constant variance, known as heteroscedasticity. To address this issue, the ARCH model was introduced by Engle (1982), and later the GARCH model was developed by Bollerslev (1986) as a generalized form of the ARCH model.

The general form of the ARCH(p) model is as follows [9]:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_0 a_{t-p}^2$$

The general form of the ARCH(p) model is as follows [9]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2$$

2.2. GARCH in Mean (GARCH-M) Model

If the conditional variance or standard deviation is incorporated into the mean equation, the resulting model is referred to as the GARCH in Mean (GARCH-M) model [10]. The GARCH(p, q)-M model can be defined as follows:

$r_t = \mu + c\sigma_t^2 + a_t$

where

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2$$

Here, μ and c are constants. A positive c indicates that returns are positively affected by past volatility. Other specifications for the risk premium commonly used in the literature include [9]:

$r_t = \mu + c\sigma_t + a_t$ and

and

$$r_t = \mu + c\log(\sigma_t^2) + a_t$$

The formulation of the GARCH-M model suggests the existence of serial correlation in the return series. This serial correlation is demonstrated by the volatility process. The existence of a risk premium implies that the historical returns of a stock exhibit serial correlation.

2.3. Quasi Maximum Likelihood Estimation

Tsay [9] offers the application of the Quasi Maximum Likelihood (QML) method for time series analysis in cases where the error terms do not follow a normal distribution. The QML approach still utilizes the maximum likelihood method as its foundation, so the computation of quasi covariance variance relies on values obtained from the maximum likelihood estimation (MLE) method.

Within the ARCH/GARCH specification, it is still possible to produce a valid model and consistent parameter estimates by using the QML method, which maximizes the log-likelihood function through linear forecasting of the squared residuals. With this method, the consistency of standard errors is maintained even if the distributional assumptions are violated. The parameter estimation model using QML is given by:

$$f(\epsilon_1, \epsilon_2, \dots, \epsilon_T|\alpha) = \frac{1}{\sqrt{2\pi\sigma_t^2}}\exp\left(\frac{-\epsilon_t^2}{2\sigma_t^2}\right)$$

III. RESEARCH METHODS

The data used in this study are secondary data, specifically stock data of PT Indofood CBP Tbk. (ICBP.JK), obtained from www.finance.yahoo.com covering the period from January 1, 2024, to December 31, 2024. This study uses return data of the stock, comprising a total of 236 observations.

The data in this study are processed using R software. The steps taken to analyze the data are as follows:

1. Convert the stock price data of ICBP.JK into return data.
2. Identify the ARIMA model based on the time series plot to determine whether the data are stationary. Once stationarity is achieved, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are generated to identify the appropriate model.
3. Estimate the parameters of the ARIMA model.
4. Perform model verification by conducting residual independence tests and residual normality tests. If necessary, other models can be considered through underfitting and overfitting analysis.
5. Perform the Lagrange Multiplier (LM) test to determine whether there is an ARCH effect in the model.
6. Identify the appropriate ARCH and GARCH models.
7. Identify the GARCH-M model.
8. Estimate the model parameters using the Quasi Maximum Likelihood (QML) method.
9. Conduct another Lagrange Multiplier (LM) test to verify if there is still an ARCH effect remaining in the model.
10. Verify the GARCH-M model to select the best-fit model.
11. Forecast the volatility of PT Indofood CBP Tbk.'s stock using the best model.

IV. RESEARCH FINDINGS AND DISCUSSION

The observational data consist of the daily closing stock prices of PT Indofood CBP Tbk. from January 1, 2024 to December 31, 2024, using active trading days from Monday to Friday. The data analyzed are the return data of the closing stock prices. The chart of the company's stock prices can be seen in Figure 1, while the stock returns are shown in Figure 2.

In Figure 2, it can be observed that the return plot of PT Indofood CBP Tbk.'s stock is stationary in the mean. This is indicated by the fact that the average of the observation series over time remains constant (fluctuating around a central value).

Fig 1. Stock Prices Plot

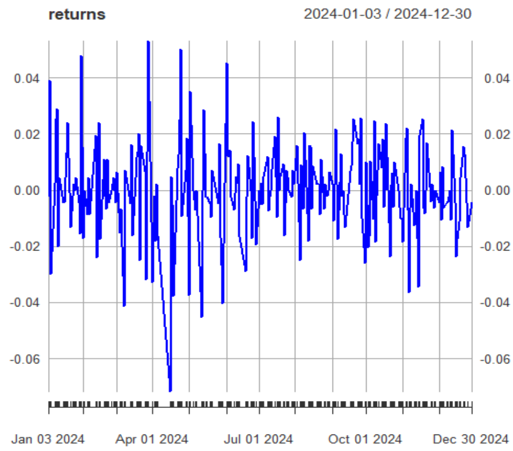

Fig 2. Stock Returns Plot

To provide an initial overview of the data used in this study, a descriptive statistical analysis was conducted. This analysis includes key measures such as the mean, standard deviation, minimum, maximum, skewness, and kurtosis, which offer insights into the distribution and variability of the return series. The complete descriptive statistics of the research data are presented in the Table 1.

Table 1. Statistics Descriptives of Price and Return

Statistics	Price	Return
Number of Data	237	236
Mean	11263.71	0.00027905
Standard Deviation	691.9917	0.01682765
Variance	478852.5	0.00028317
Skewness	0.1012407	-0.20530410
Kurtosis	-0.6779047	1.67403100

The descriptive statistics of ICBP’s stock prices provide an initial understanding of the characteristics of the dataset, which consists of 237 observations. The mean value of 11263.71 indicates the average level of the observed data, suggesting a relatively high central tendency in the series. The standard deviation of 691.99, along with the variance of 478,852.5, reflects a moderate level of dispersion around the mean, implying that the data exhibit noticeable fluctuations over the observed period.

The skewness value of 0.10 suggests that the distribution of the data is approximately symmetric, with a slight positive skew. This means that the dataset has a minor tendency for values to be concentrated on the left side, with a few larger observations on the right. Meanwhile, the kurtosis value of -0.68 indicates that the distribution is platykurtic, which implies that the data have lighter tails and a flatter peak compared to a normal distribution. In other words, extreme values (outliers) are less likely to occur within this dataset.

Overall, the descriptive statistics of ICBP’s stock prices demonstrate a dataset with moderate volatility, near-symmetrical distribution, and relatively fewer outliers, providing a stable basis for further time series modeling and volatility analysis.

The descriptive statistics of the return series, based on 236 observations, provide valuable insights into the distribution and characteristics of the data. The mean return is 0.00027905, indicating a very small average daily return, which is typical for financial time series data, particularly when using daily stock returns. Although the average return is positive, its magnitude suggests minimal daily gains over the observed period.

The standard deviation of 0.01682765 reflects the level of volatility present in the return series. This indicates a moderate degree of fluctuation around the mean, which is consistent with the nature of stock returns in emerging markets, where volatility tends to be higher compared to developed markets. The variance is 0.00028317, further confirming the variability in returns.

The skewness value of -0.20530410 suggests a slight negative skew in the distribution of returns. This implies that the return series exhibits a tendency for more extreme negative returns compared to positive ones, although the skewness is relatively small and close to zero, indicating near-symmetry.

The kurtosis value of 1.67403100 is lower than the normal distribution kurtosis of 3, indicating a platykurtic distribution. This means the return series has lighter tails and a flatter peak than a normal distribution, implying fewer occurrences of extreme returns or outliers.

Overall, the descriptive statistics indicate that the return series of the stock exhibits low average returns, moderate volatility, slight negative skewness, and lower tail risk, suggesting the data is relatively stable but still exhibits characteristics typical of financial time series.

The first step in ARIMA modeling is model identification to determine the most appropriate model for the stock return data. This identification process can be observed through the ACF and PACF correlograms. The preliminary results suggest that the stock return data follows an ARIMA(2,0,1) with zero mean model.

After obtaining the preliminary model, the next step is parameter estimation. The results of the parameter estimation are presented in Table 2.

Table 2. ARIMA Parameter amd Signicance Test

Parameter	Estimation	p-value	Result
AR1	-0.6975	0.000733	Significant
AR2	-0.1859	0.004741	Significant
MA1	0.5507	0.006419	Significant

All parameters in the ARIMA model are statistically significant, as each p-value is below the 5% significance level ($\alpha = 0.05$). AR(1) and AR(2) terms show negative coefficients, indicating inverse relationships with past observations. The MA(1) term is positive, reflecting a direct impact of past error terms on the current value. This suggests the ARIMA model has well-defined dynamics and can capture the time series' autocorrelation structure effectively.

Table 3. ARCH LM and Box-Ljung Test Results for ARIMA Model Residuals

Test	p-value	Result
ARCH LM Test	0.04697	There is evidence of ARCH effects.
Box-Ljung Test on Residuals	0.00706	Significant autocorrelation in squared residuals, indicating heteroskedasticity

Both the ARCH LM Test and the Box-Ljung Test on the squared residuals indicate the presence of heteroskedasticity in the residuals of the ARIMA model. The ARCH LM Test yields a p-value of 0.04697, leading to the rejection of the null hypothesis of no ARCH effects at the 5% significance level.

Similarly, the Box-Ljung Test on squared residuals results in a p-value of 0.007065, confirming the presence of significant autocorrelation in the variance of residuals. These findings strongly suggest that the residuals exhibit time-varying volatility, which is not captured by the ARIMA model alone. Therefore, it is appropriate to fit a GARCH or GARCH-M model to account for the changing variance over time and to better model the volatility dynamics of the time series. Then, we have to proceed with estimating a GARCH(1,1) or GARCH-M model on the residuals or return.

Table 4 shows a summary of the ARIMA-GARCH-M estimation results for ICBP.JK returns in 2024. And Table 5 shows the assumptions diagnostics of the ARIMA-GARCH-M for ICBP.JK returns in 2024.

Table 4. ARIMA(2,0,1)-GARCH(1,1)-M Model Estimation

Parameter	Estimation	p-value	Result
ω	0.000051	0.00947	Significant
α	0.469173	0.04918	Significant
β	0.440526	0.02823	Significant

Table 5. Diagnostic Test Results for ARIMA-GARCH-M Model

Test	p-value	Result
Ljung-Box Test on Standardized Residuals (Lag 14)	0.4623	No serial correlation
Ljung-Box Test on Standardized Squared Residuals (Lag 9)	0.2804	No ARCH effects remaining
ARCH LM Test	0.1030	No further ARCH effects

The returns are modeled with an ARIMA(2,0,1) process. Both AR(1), AR(2), and MA(1) terms are statistically significant ($p < 0.01$), indicating a strong autoregressive and moving average structure in return dynamics. Volatility is captured by a standard GARCH(1,1) model, with both the ARCH (α1) and GARCH (β_1) terms being significant ($p < 0.05$). This shows that volatility clustering exists in ICBP returns, where large changes are likely followed by large changes. The coefficient of the ARCH-M term is negative and statistically significant ($p = 0.0934$). This implies that the conditional variance has a significant direct impact on expected returns in this model.

Ljung-Box Tests on both residuals and squared residuals indicate no significant autocorrelation remaining in the model (p-values > 0.05). This suggests that the ARIMA-GARCH-M specification has successfully captured the dynamics in the mean and variance. ARCH LM Test shows no remaining ARCH effects at lags up to 7 ($p = 0.1030$), confirming that conditional heteroskedasticity has been adequately modeled.

The sum of α_1 (0.469) and β_1 (0.441) is approximately 0.91, implying high volatility persistence. This means volatility shocks take time to dissipate, which is consistent with financial market behavior.

The ARIMA(2,0,1)-GARCH(1,1)-M model is an appropriate specification for modeling and forecasting the volatility of ICBP returns in 2024. Despite the ARCH-M term being insignificant, the GARCH component captures volatility clustering effectively. Residual diagnostics confirm no remaining autocorrelation or ARCH effects. The high volatility persistence suggests that risk management strategies should consider the prolonged impact of market shocks. The model can be used for forecasting volatility, Value-at-Risk (VaR) calculations, or as an input in portfolio optimization.

After successfully estimating the ARIMA(2,1,1)-GARCH(1,1)-M model for the ICBP stock returns, we proceed with generating out-of-sample forecasts for the next 10 trading days. The forecast includes both the expected returns (mean equation forecast) and the conditional volatility (variance equation forecast), which represents the predicted risk level or uncertainty in the market.

The forecasted values are essential for investors and risk managers to understand potential price movements and volatility dynamics in the short-term future. Higher conditional volatility signals increased risk, while the expected returns give insight into the potential direction of asset prices. Table 6 and Figure 3 are the 10-day ahead forecast, showing the predicted returns and their corresponding conditional standard deviations (volatility).

Table 6. Forecast: Expected Returns & Conditional Volatility

Time	Forecasted Return	Forecasted Volatility
T+1	0.0033999	0.01330
T+2	-0.0005439	0.01456
T+3	0.0008605	0.01561
T+4	0.0005958	0.01651
T+5	0.0004635	0.01729
T+6	0.0006126	0.01796
T+7	0.0005031	0.01856
T+8	0.0005424	0.01909
T+9	0.0005215	0.01955
T+10	0.0005171	0.01997

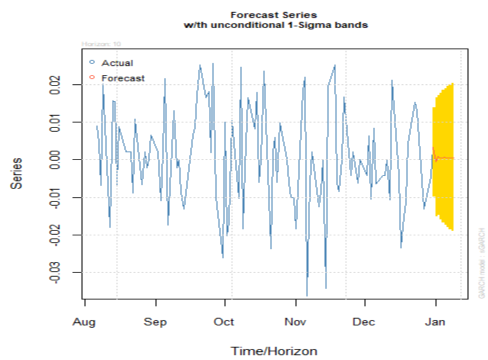

Fig 3. Forecast: Expected Returns

The expected returns are relatively close to zero over the next 10 days. The first forecasted return (T+1) shows a slight positive return of 0.0034, followed by fluctuations around zero. These results are typical for financial return series, which often display low and stationary expected returns in the short term. The conditional volatility is increasing over time. It starts at 0.01330 (or 1.33%) at T+1. It rises to 0.01997 (or 1.997%) by T+10. This gradual increase in volatility suggests the presence of volatility clustering, a common feature in financial time series, where past high volatility tends to lead to future high volatility.

The GARCH(1,1) process forecasts that volatility will increase slightly in the forecast horizon before stabilizing, consistent with the persistence of volatility estimated in your model.

Higher forecasted volatility implies greater risk in future periods, especially towards the end of the 10-day horizon. The mean forecasted returns are small, suggesting neutral or slightly positive expectations, but the increasing volatility warns of heightened uncertainty.

The 10-step ahead GARCH-M forecast for ICBP returns shows relatively stable and low expected returns, with an increasing pattern of conditional volatility. This indicates rising risk levels over the forecast horizon, potentially due to volatility clustering. Investors should remain cautious, as higher predicted volatility may lead to larger fluctuations in returns.

V. CONCLUSION

The modeling and analysis of PT Indofood CBP Sukses Makmur Tbk (ICBP.JK) returns for the year 2024, using the ARIMA-GARCH-M approach, provide several insightful findings regarding the stock's return behavior and volatility dynamics. The best-fitted mean equation was identified as an ARIMA(2,0,1), indicating that the return series is influenced by two autoregressive terms and one moving average component. All estimated parameters for the AR and MA terms were found to be statistically significant, suggesting the presence of autocorrelation in the return series. This highlights the predictive power of past returns and error terms in explaining the current return movements of ICBP.

In terms of volatility modeling, the GARCH(1,1)-M model with a Student-t distribution was selected due to its ability to capture the heavy-tailed nature of financial return distributions. The model estimates show that both ARCH (α_1 = 0.4691) and GARCH (β_1 = 0.4405) parameters are positive and statistically significant under conventional standard errors. The sum of these parameters, approximately 0.91, indicates high volatility persistence, meaning that shocks to the volatility process have long-lasting effects. However, the ARCH-in-Mean (ARCH-M) parameter was not statistically significant, suggesting that volatility does not directly influence the expected return of ICBP during the analyzed period.

The residual diagnostics, including Ljung-Box and ARCH LM tests, confirm that the standardized residuals and squared residuals exhibit no significant autocorrelation or remaining ARCH effects, implying that the model adequately captures the volatility clustering present in the data. Additionally, the 10-day-ahead volatility forecast indicates a gradual increase in conditional standard deviation, reflecting a potential rise in market uncertainty.

Overall, the ARIMA-GARCH-M model demonstrates its effectiveness in modeling and forecasting ICBP stock returns and volatility. These findings provide valuable insights for investors and risk managers by offering a robust tool to anticipate future volatility and manage investment risks in the Indonesian stock market, particularly in the consumer goods sector.

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