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Analyzing Rupiah-USD Exchange Rate Dynamics: A Study with ARCH and GARCH Models

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Abstract*—The study aims to analyze the volatility of the Rupiah-USD exchange rate and predict future fluctuations using the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The exchange rate data, spanning from January 2010 to December 2023, is sourced from Bank Indonesia (BI) and adheres to the Jakarta Interbank Spot Dollar Rate (JISDOR) regulations, focusing solely on business days. ARCH and GARCH models are widely applied in financial time series analysis because they capture and forecast time-varying volatility. This study analyzes historical exchange rate data to evaluate the persistence of volatility and detect any structural breaks that could impact future exchange rate behavior. The findings reveal that both models effectively capture the volatility of the Rupiah-USD exchange rate, but the GARCH (1,1) model demonstrates superior forecasting accuracy. This model's ability to account for long-term volatility clustering makes it particularly useful for predicting exchange rate dynamics. The research contributes to a deeper understanding of the factors driving exchange rate fluctuations, offering valuable insights for policymakers, investors, and businesses. These insights can help stakeholders manage exchange rate risks more effectively within Indonesia's open economy, where global financial conditions and external shocks significantly shape currency movements. The study emphasizes the importance of using advanced econometric models for accurate volatility predictions and informed decision-making.

***Keywords*—ARCH; GARCH; exchange rate; Rupiah-USD.**

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I. Introduction

The exchange rate is one of the most crucial economic indicators in the global economy, particularly for developing countries like Indonesia, which heavily depend on international trade and foreign capital flows. The exchange rate of the Indonesian Rupiah against the United States Dollar (USD) plays a vital role in determining the prices of goods and services, macroeconomic stability, and monetary policy decisions. As the world's reserve currency, the USD is the most widely used currency in global trade transactions, making fluctuations in the Rupiah-USD exchange rate significantly impactful across various sectors of the Indonesian economy [1].

Exchange rate volatility is a primary concern for policymakers, market participants, and companies operating in international trade sectors. Sudden changes in exchange rates can affect the prices of imported goods, production costs, and export competitiveness. In Indonesia, external factors such as global commodity price changes, monetary policies in advanced economies, and international capital flows often influence exchange rate fluctuations. Additionally, domestic factors like inflation, interest rates, and political stability also play a role in determining exchange rate volatility [2].

Indonesia is particularly sensitive to exchange rate volatility as a country highly dependent on imported raw materials and energy. A depreciation of the Rupiah against the USD leads to higher prices for imported goods, including raw materials and essential commodities, which can trigger inflation and increase the cost of living for the population. Conversely, a Rupiah appreciation may reduce the prices of imported goods but could also diminish the competitiveness of Indonesian exports in the global market [3]. Therefore, maintaining exchange rate stability is crucial to sustaining price stability and ensuring long-term economic growth.

Exchange rate volatility also influences investment decisions for domestic and foreign investors. Uncertainty in exchange rate movements increases investment risk, especially for investors with multiple currencies. For example, multinational companies operating in Indonesia must account for exchange rate risks in their financial planning, as exchange rate volatility can significantly impact profit margins. Thus, a better understanding of exchange rate volatility dynamics is essential for market participants to manage risks and make informed decisions in the face of uncertainty [4].

A range of domestic and international factors drive the volatility of the Rupiah-USD exchange rate. One major factor is the fluctuation of global commodity prices, particularly oil, coal, and palm oil. As an importer of oil and an exporter of commodities, Indonesia is highly affected by these price movements. A decline in commodity prices can lead to currency depreciation due to a reduction in export revenues while rising commodity prices can strengthen the Rupiah by increasing foreign exchange inflows [5].

Additionally, monetary policies in advanced economies, especially in the United States, significantly influence Rupiah exchange rate movements. When the Federal Reserve raises interest rates, capital tends to flow out of emerging markets, including Indonesia, toward safer assets in developed countries, which can lead to currency depreciation in emerging markets. On the other hand, expansionary monetary policies in advanced economies, such as lowering interest rates, can encourage capital inflows into Indonesia, thus strengthening the Rupiah [6].

Domestic factors such as inflation and interest rates also play a crucial role in determining exchange rates. High inflation tends to erode the purchasing power of the domestic currency, leading to currency depreciation. Meanwhile, an increase in interest rates by Bank Indonesia can attract capital inflows, ultimately strengthening the Rupiah. However, higher interest rates can also constrain domestic economic growth by raising borrowing costs for businesses and households [7].

Researchers have developed various statistical models to understand and predict exchange rate volatility. One of the most widely used models is the Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Robert Engle in 1982. The ARCH model captures time-varying volatility patterns by accounting for the error variance (residual) from previous periods. However, the ARCH model has limitations in capturing long-term volatility trends [8].

In response, Tim Bollerslev extended the ARCH model by developing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in 1986. The GARCH model is more flexible, incorporating the conditional variance from previous periods and allowing volatility to be influenced by the residuals from prior periods. The GARCH model effectively captures the phenomenon of volatility clustering, where high volatility periods are followed by more high volatility and low volatility periods are followed by more low volatility. This advantage makes the GARCH model highly suitable for predicting volatility in financial markets, including exchange rate volatility [9].

Earlier studies have demonstrated that the ARCH and GARCH models effectively predict exchange rate volatility in emerging markets like Indonesia. For example, research by Aghion et al showed that the ARCH and GARCH models could predict Rupiah exchange rate volatility with high accuracy, particularly during periods of economic instability [10]. Another study by Ashour and Yong emphasized that Rupiah exchange rate volatility has a significant impact on Indonesia's financial stability, primarily through capital flows and price stability channels [11].

When designing monetary policies, understanding exchange rate volatility is critical for economic policymakers, particularly for Bank Indonesia. High volatility can trigger inflation and affect the stability of the financial system. Therefore, Bank Indonesia must continuously monitor exchange rate movements and take preventive measures, such as foreign exchange market intervention or interest rate adjustments, to maintain Rupiah stability [12].

Moreover, the government must consider the impact of exchange rate volatility in managing foreign debt. As a country with substantial exposure to foreign currency-denominated debt, exchange rate fluctuations can increase the government's debt burden in local currency terms, potentially affecting fiscal balance. Consequently, risk mitigation strategies, such as hedging, are essential to managing exchange rate fluctuation risks [13].

To manage their financial risks, multinational companies operating in Indonesia must also understand the dynamics of exchange rate volatility. Uncertainty in exchange rate movements can affect the prices of goods and services, production costs, and company profits. Therefore, companies should utilize financial instruments such as forward contracts or currency options to hedge against unforeseen exchange rate risks [14].

This research is significant because high exchange rate volatility can lead to severe economic instability. In Indonesia, increased Rupiah volatility against the USD affects import prices, export competitiveness, and domestic inflation. Understanding the patterns and factors influencing this volatility allows policymakers to design more effective monetary and fiscal policies to maintain economic stability.

Furthermore, this research contributes to the literature on applying the ARCH and GARCH models in developing countries, particularly Indonesia. Most previous studies employing these models have been conducted in developed countries with more stable financial markets, whereas studies in developing countries still need to be explored. Thus, this research not only offers relevant insights for Indonesia but can also serve as a reference for analyzing volatility in other developing countries [3].

Complex macroeconomic factors, such as inflation, interest rates, and commodity prices, often drive exchange rate volatility. In Indonesia, changes in monetary policies, global oil price shocks, and fluctuations in international capital flows are frequently the main drivers of Rupiah-USD volatility. Economists and policymakers' primary challenge is the inability to predict sudden and unexpected changes in this volatility.

II. MATERIALS AND METHOD

The study aims to analyze the volatility of the Indonesian Rupiah exchange rate against the United States Dollar (USD) using the Autoregressive Conditional Heteroskedasticity

(ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) statistical models. These two models frequently predict volatility in financial time series data, particularly in time-varying volatility or volatility clustering. These methods are well-suited for financial volatility data, such as exchange rates, which often exhibit high volatility during periods of economic uncertainty and lower volatility under stable economic conditions [15].

The research methodology comprises several stages: data collection, data processing, volatility modeling with ARCH and GARCH, and model evaluation. In addition, this study explores the influence of macroeconomic variables, such as inflation, interest rates, and global oil prices, on the volatility of the Rupiah against the USD.

1) Data Collection: The initial stage of this study involves collecting daily exchange rate data for the Rupiah against the USD. The data is sourced from the official records of Bank Indonesia (BI). The data spans from January 2010 to December 2023 and only includes exchange rate data for business days, following Bank Indonesia's JISDOR (Jakarta Interbank Spot Dollar Rate) regulations. This time frame is selected to capture exchange rate volatility dynamics, including significant global economic events, such as the global financial crisis and the COVID-19 pandemic, which substantially impacted exchange rate movements [15].

2) Data Processing: After data collection, the next step involves processing the data to ensure it meets ARCH and GARCH modeling requirements. Since both models require stationary data, the first step in data processing is transforming the exchange rate data into logarithmic returns. The daily return is calculated using the formula [16]:

$$\text{Return}_t = ln\left(\frac{\text{Rate}_t}{\text{Rate}_{t-1}}\right) \tag{1}$$

where Rate_t represents the Rupiah-USD exchange rate on day t^{th}, and Rate_{t-1} is the exchange rate on the previous day. Using logarithmic returns helps address non-stationarity and asymmetric distribution issues in exchange rate data.

After calculating daily returns, a stationarity test is conducted using the Augmented Dickey-Fuller (ADF) test to ensure that the return data does not contain a unit root. The ADF test is a statistical procedure used to determine whether a time series is stationary or non-stationary [17]. The results of this test will indicate whether additional transformations are needed to render the data stationary before applying the ARCH and GARCH models [18].

3) Volatility Modeling with ARCH and GARCH: Once the daily return data is confirmed to be stationary, the next step involves modeling volatility using the ARCH and GARCH models. These models are employed to predict exchange rate volatility based on historical patterns in residual variance. The ARCH model allows the conditional variance at a given time to be influenced by the squared residuals from previous periods. The GARCH model extends the ARCH model by incorporating the conditional variance from previous periods as an additional variable.

To perform the complete analysis of the ARCH/GARCH models, data processing is conducted using statistical software. In this case, R software is used to perform the GARCH modeling. After estimating the model, the ARCH and GARCH parameters are analyzed to determine the magnitude of the influence of squared residuals and conditional variance on exchange rate volatility [19].

4) Model Evaluation: After estimating the ARCH and GARCH models, the next step is to evaluate the model's performance using statistical criteria such as the Akaike Information Criterion (AIC) [20], Bayesian Information Criterion (BIC), Shibata Criterion, and Hannan-Quinn Criterion. These criteria compare model performance and select the model that provides the best predictive outcomes. The criteria assess the balance between model fit and complexity, with lower AIC and BIC values indicating a better model for predicting exchange rate volatility [21]. In addition, residual tests are performed to ensure no autocorrelation remains in the residuals after the estimated ARCH and GARCH models.

5) Model Validation and Volatility Prediction: Once the ARCH and GARCH models have been evaluated, the final step is to use the selected model to predict the future volatility of the Rupiah against the USD. Volatility predictions are made using out-of-sample data (data outside the period used for model estimation) to test how well the model can forecast future volatility. The predicted volatility is then compared with actual volatility to determine the model's accuracy.

III. Results and Discussion

A. Descriptive Data

As shown in Figure 1, in early 2020, the graph indicates a sharp spike in the Rupiah exchange rate, surpassing 16,500 IDR per USD. This drastic increase was likely caused by the COVID-19 pandemic, which severely disrupted the global economy. This surge reflects a significant depreciation of the Rupiah against the USD, indicating that the Rupiah lost value quickly. The peak was in early 2020 when the Rupiah gradually strengthened. It stabilized around 14,500-15,000 IDR per USD by the end of 2020, signaling a recovery after the initial instability caused by the pandemic.

During this period, the Rupiah exchange rate appeared relatively stable, though still subject to fluctuations. The exchange rate ranged between 14,200 and 14,800 IDR per USD, reflecting a phase of financial market stabilization after the uncertainty at the onset of the pandemic. By mid-2022, the Rupiah had again shown a significant depreciation. It declined sharply, reaching more than 15,500 IDR per USD by the end of 2022 and into early 2023. External factors such as global monetary policy, interest rate hikes by the Federal Reserve, and global economic uncertainty likely contributed to the weakening of the Rupiah during this period.

As presented in Figure 2, a decomposition process is conducted to further analyze the data's characteristics. Figure 2 illustrates the data's decomposition into three components. The trend shows a long-term pattern, with values declining until mid-2021 and rising through 2023. The seasonal part displays periodic fluctuations, representing recurring seasonal variations over time. Lastly, the residual or random component reflects the variability that cannot be explained by the trend or seasonal components, indicating irregular noise in the data.

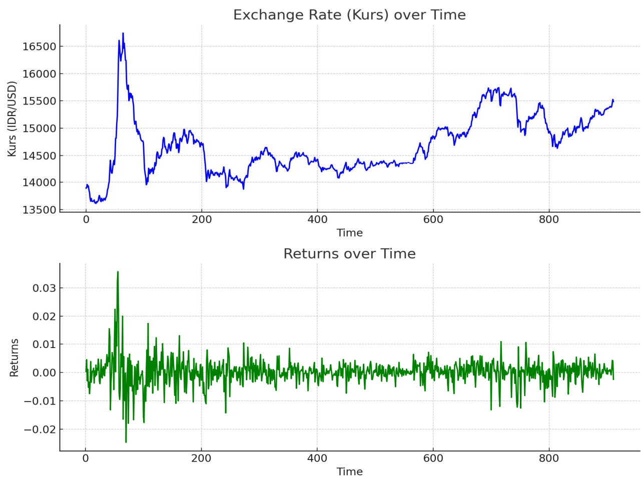

Fig. 1 Rupiah Exchange Rate Against the U.S. Dollar

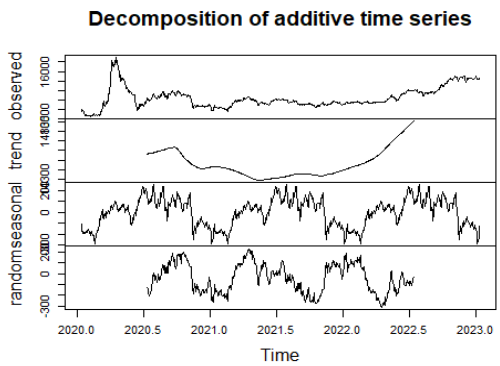

Fig. 2 Data Decomposition of Rupiah Exchange Rate Against the U.S. Dollar

The next step involves calculating the ARCH and GARCH models. For this, the data is transformed into daily returns, which are calculated using the formula:

$$Return_t = ln\left(\frac{Rate_t}{Rate_{t-1}}\right) \quad (2)$$

Figure 3 shows the distribution of the returns, which is approximately normal. It indicates that most returns are clustered around the mean, with a few outliers on both ends. However, volatility remains evident from the wide spread of returns, ranging from significant negative to positive values. The next step is to proceed with inferential analysis using the ARCH/GARCH models to capture the data's dynamic volatility and provide predictions about future fluctuations in the Rupiah-USD exchange rate.

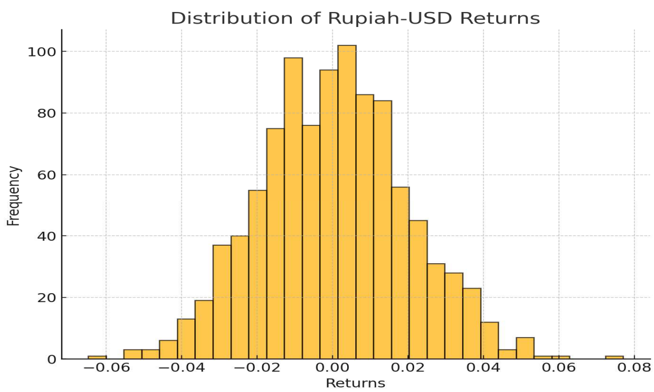

Fig. 3 Plot of Rupiah Return Distribution Against USD

B. *ARCH Modeling*

To model ARCH/GARCH, it is first necessary to test whether the data exhibits ARCH effects (Autoregressive Conditional Heteroskedasticity), meaning the variance depends on past errors. The initial step is conducting the ARCH-LM test to check for heteroskedasticity. The output from the R software shows:

```
        ARCH LM-test; Null hypothesis: no ARCH effects

data:  returns
Chi-squared = 230.82, df = 5, p-value < 2.2e-16
```

In the ARCH-LM Test, the p-value $< 2.2 \times 10^{-16}$, which is very small (< 0.05), indicating the rejection of the null hypothesis, meaning there is a significant ARCH effect in the data. This suggests heteroskedasticity in the residuals, and an ARCH model is needed to capture the time-varying volatility. The next step involves testing the ARCH (1) model. The R software output shows:

```
Call:
garch(x = returns, order = c(0, 1))

Model:
GARCH(0,1)

Residuals:
     Min       1Q   Median       3Q      Max
-7.33972 -0.42390  0.08447  0.54174  5.20581

Coefficient(s):
    Estimate  Std. Error  t value Pr(>|t|)
a0 1.158e-05   3.221e-07    35.94   <2e-16 ***
a1 4.247e-01   3.836e-02    11.07   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The fitted model is ARCH(1) (or GARCH(0,1)), with the estimation results:

- a_0 (constant) = 1.158×10^{-5} (with a t-value of 35.94, p-value $< 2 \times 10^{-16}$), which is highly significant.
- a_1 (ARCH term) = 0.4247 (with a t-value of 11.07, p-value $< 2 \times 10^{-16}$), also highly significant.

Both parameters are statistically significant (p-value $< 2 \times 10^{-16}$), indicating that the ARCH(1) model explains the volatility pattern in the data well. The parameter a1 of 0.4247 shows that previous period shocks significantly influence volatility.

The next step is to check for autocorrelation in the residuals.

```
Diagnostic Tests:
        Jarque Bera Test

data:  Residuals
X-squared = 1566.5, df = 2, p-value < 2.2e-16


        Box-Ljung test

data:  Squared.Residuals
X-squared = 0.5334, df = 1, p-value = 0.4652
```

The results from the Jarque-Bera Test show a very small p-value (p-value $< 2.2 \times 10^{-16}$), meaning the residuals are not normally distributed. This could indicate the presence of outliers or a heavier tail distribution than normal. Similarly, the Box-Ljung Test reveals no significant autocorrelation in the squared residuals, indicating that the ARCH model successfully captures the heteroskedasticity patterns in the data.

Although the ARCH(1) model provides significant results for modeling volatility, the residuals exhibit potential autocorrelation that the model does not fully capture. This suggests that a GARCH or more complex variation may be more appropriate. Therefore, a GARCH model is implemented.

C. GARCH Modeling

The first step is specifying the GARCH(1,1) model, and the results are as follows:

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(0,0,0)
Distribution    : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000087    0.000101  0.85825 0.390753
omega   0.000000    0.000001  0.32982 0.741533
alpha1  0.127398    0.046872  2.71803 0.006567
beta1   0.851631    0.044450 19.15950 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.000087    0.000294 0.294921  0.76806
omega   0.000000    0.000031 0.012361  0.99014
alpha1  0.127398    1.087430 0.117156  0.90674
beta1   0.851631    1.076239 0.791303  0.42877
```

From the analysis, the parameter μ represents the average return in the model. The estimate of 0.000087 indicates that the average return is near zero, which is common in GARCH models, where long-term average returns typically approach zero. The p-value of 0.390753 suggests this value is not statistically significant (above the 0.05 significance level), meaning the mean return is not significantly different from zero.

The ω parameter is the constant in the GARCH equation that describes long-term conditional variance. The very small estimate of ω (0.000000) suggests that the long-term variance in this model is very low, with a p-value of 0.741533, indicating that this parameter is also not statistically significant. This implies that the model relies more on the ARCH and GARCH components to explain volatility rather than the ωconstant.

The α_1 parameter measures the volatility response to shocks from the previous period. The estimate of 0.127398 indicates that 12.74% of the previous period's volatility shock affects current volatility, with a p-value of 0.006567, making it statistically significant at the 0.01 level (below 0.05). This shows that past volatility shocks have a significant effect on current volatility.

The β_1 parameter measures volatility persistence, or how much past volatility influences current volatility. The estimate of 0.851631 suggests that about 85% of past volatility carries over into the present period, indicating high persistence in volatility. The p-value of 0.000000 shows this parameter is highly statistically significant. Thus, past conditional volatility strongly influences future volatility.

D. Model Evaluation

The next step is evaluating the model using several criteria. The results are as follows:

```
LogLikelihood : 3846.482

Information Criteria
------------------------------------

Akaike       -8.4357
Bayes        -8.4146
Shibata      -8.4358
Hannan-Quinn -8.4277
```

For the Akaike Information Criterion (AIC), the lower the AIC value, the better the model. The analysis yields an AIC value of -8.4357, indicating that the fitted GARCH model is very good, as the low and negative AIC value suggests a good balance between model complexity and fit. Similarly, lower values indicate better Bayesian Information Criterion (BIC) models. The BIC value of -8.4146 is close to the AIC value but slightly larger (less negative). This suggests that BIC is slightly more conservative than AIC, though the negative value still indicates a good model.

The Shibata Criterion value of -8.4358 is nearly identical to the AIC value, showing agreement that the GARCH(1,1) model provides an excellent balance between fit and complexity. For the Hannan-Quinn Criterion (HQIC), the value of -8.4277 is between the AIC and BIC values. This suggests that HQIC offers a more moderate criterion for complexity than BIC but is larger than AIC. The results consistently show that the model is a good fit without being overly complex. Overall, all criteria provide very similar negative values, indicating that the GARCH(1,1) model balances fit and the number of parameters.

E. Diagnostic Testing

The next step is conducting diagnostic tests to determine whether the GARCH model has captured all the volatility patterns in the data (Ljung-Box Test, ARCH-LM Test, etc.).

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic   p-value
Lag[1]                      22.77 1.822e-06
Lag[2*(p+q)+(p+q)-1][2]     22.79 8.230e-07
Lag[4*(p+q)+(p+q)-1][5]     24.06 1.461e-06
d.o.f=0
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                      4.634 0.03135
Lag[2*(p+q)+(p+q)-1][5]     5.241 0.13492
Lag[4*(p+q)+(p+q)-1][9]     6.884 0.20908
d.o.f=2

Weighted ARCH LM Tests
------------------------------------
            Statistic Shape Scale P-Value
ARCH Lag[3]    0.1865 0.500 2.000  0.6658
ARCH Lag[5]    0.8914 1.440 1.667  0.7654
ARCH Lag[7]    2.4310 2.315 1.543  0.6267

     Nyblom stability test
     ------------------------------------
     Joint Statistic:  28.7004
     Individual Statistics:
     mu      0.2196
     omega  13.6454
     alpha1  0.3736
     beta1   0.2014

     Asymptotic Critical Values (10% 5% 1%)
     Joint Statistic:         1.07 1.24 1.6
     Individual Statistic:    0.35 0.47 0.75

     Sign Bias Test
     ------------------------------------
                        t-value   prob sig
     Sign Bias           0.6277 0.5303
     Negative Sign Bias  1.2434 0.2140
     Positive Sign Bias  1.0215 0.3073
     Joint Effect        2.8880 0.4092
```

The analysis results indicate that for the Ljung-Box Test, the test statistics at various lags (1, 2, and 5) are significant (p-values < 0.01), suggesting autocorrelation in the standardized residuals. This implies that the model may have yet to fully capture all dynamics in the data.

For the ARCH-LM test, the large p-value (p-value > 0.05) indicates no remaining ARCH effects. This means the GARCH model has adequately captured the conditional heteroskedasticity in the data. Similarly, for the Nyblom Stability Test, the joint statistic (28.7004) is much larger than the critical value, indicating parameter instability. The individual statistics for ω show substantial instability, suggesting that the model parameters may not be constant over time. The Sign Bias Test results show no significant bias (Sign Bias, Negative Sign Bias, Positive Sign Bias, or Joint Effect), indicating no asymmetry or bias in the model's response to positive or negative shocks.

Overall, the GARCH(1,1) model effectively captures volatility clustering (as indicated by the significance of α_1 and β_1), but there is evidence of parameter instability and residual autocorrelation. Furthermore, the goodness-of-fit tests indicate that the model specification can be improved.

F. Discussions

The analysis using the GARCH (1,1) model on the volatility of the Rupiah exchange rate against the USD provides essential insights into the dynamics of exchange rate volatility faced by Indonesia during the analysis period [22]. This discussion will delve deeper into the interpretation of the observed volatility, the relevance of influencing factors, and the implications of these findings in the context of monetary policy and financial markets [23].

From the GARCH (1,1) model estimation, it is evident that the volatility of the Rupiah against the USD exhibits a high degree of persistence. This is indicated by the high value of the β_1 coefficient (0.85). Persistent volatility means that if there is a shock to volatility in a given period, the effects of that shock are likely to persist over several subsequent periods [24]. This is consistent with the phenomenon of volatility clustering, where periods of high volatility are followed by further periods of high volatility, and the same applies to low volatility.

This phenomenon is commonly observed in global financial markets, especially during periods of global economic uncertainty. For instance, during financial crises or changes in U.S. monetary policy, exchange rate volatility in emerging markets, including Indonesia, tends to increase significantly. A study by Maharana, Panigrahi, & Chaudhury also identified similar findings in emerging markets, where high volatility during periods of instability tends to persist over the long term [25]. This suggests that exchange rate volatility is not temporary but can endure over an extended period.

The α_1 coefficient of 0.13 indicates that current volatility is significantly influenced by the squared residuals of the previous period. In other words, past shocks in exchange rate movements contribute directly to present-day volatility. This can be explained by the "shock effect" in financial markets, where high volatility on one day can cause investors to behave more cautiously in subsequent days, thus increasing volatility further.

A study by Lim and Sek [26] revealed that the GARCH model is highly effective in capturing the impact of past volatility on current volatility in emerging financial markets, including foreign exchange markets. These findings are consistent with the results of this research, where past volatility has a significant effect on the volatility of the Rupiah against the USD.

These results have important implications for risk management and monetary policy in Indonesia. For market participants and multinational companies, high and persistent exchange rate volatility can increase business and financial planning uncertainty. Companies operating in international markets should consider hedging strategies to manage exchange rate risk, especially during periods of high volatility. Additionally, for investors, high volatility can increase investment risk, particularly in the short term. High volatility often leads to unpredictable asset price movements, which may reduce foreign investor interest in investing in Indonesia [27].

From a monetary policy perspective, high volatility challenges Bank Indonesia in maintaining exchange rate stability. Bank Indonesia must closely monitor market volatility and, if necessary, intervene in the foreign exchange market to stabilize the Rupiah. One way to reduce volatility is by using interest rate tools and open market operations. For instance, raising interest rates can attract capital inflows, which helps strengthen the exchange rate. However, excessively high interest rates can also suppress economic growth, so monetary policy must be crafted carefully [28].

In addition to internal market volatility originating from Indonesia itself, the volatility of the Rupiah against the USD is also significantly influenced by external factors, such as U.S. monetary policy, changes in global commodity prices, and international capital flows. Previous research by Keefe found that monetary policy in developed countries has a significant impact on exchange rate volatility in emerging markets [29]. For example, when the Federal Reserve raises interest rates, capital flows from emerging markets to safer markets in developed countries, leading to currency depreciation and increased volatility.

Moreover, the volatility of the Rupiah is highly influenced by global commodity prices, especially oil. Indonesia is an oil-importing country, so changes in international oil prices directly impact the exchange rate. Increasing oil prices can exacerbate the trade deficit, putting pressure on the Rupiah. Conversely, declining oil prices can provide some space for currency appreciation. Research by Ito and Suzuki also confirmed that fluctuations in global oil prices are one of the critical factors influencing exchange rate volatility in Southeast Asia [30].

Based on the findings of this study, Indonesian policymakers can consider several policy recommendations to manage Rupiah-USD exchange rate volatility. First, it is essential for Bank Indonesia to continuously monitor financial market volatility and ensure that monetary policy instruments, such as interest rates and foreign exchange reserves, can be effectively utilized to stabilize the exchange rate [31]. Second, the Indonesian government needs to consider more robust strategies to shield the economy from external shocks, such as fluctuations in commodity prices and changes in monetary policy in advanced economies [32], [33].

On the other hand, companies in Indonesia engaged in international trade should develop more robust risk mitigation strategies. Using hedging instruments, such as forward contracts and currency options, can help companies reduce the impact of unexpected exchange rate fluctuations. Additionally, diversifying markets and sourcing raw materials can help companies mitigate risks associated with commodity price volatility and exchange rate changes [34].

IV. Conclusion

This study provides a detailed analysis of the volatility of the Rupiah exchange rate against the U.S. Dollar (USD) using the ARCH and GARCH model. The findings indicate that the GARCH model outperforms the ARCH model in predicting exchange rate volatility. With better performance metrics such as lower Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Shibata Criterion, and Hannan-Quinn Criterion, the GARCH model demonstrates a higher degree of accuracy in capturing long-term volatility patterns. These results have important implications for policymakers and market participants, offering a valuable tool for managing exchange rate risks.

The GARCH (1,1) model's reliable volatility predictions can be instrumental for institutions like Bank Indonesia in anticipating future fluctuations in the Rupiah's value. Exchange rate volatility can have significant consequences for inflation, interest rates, and trade balances, making it critical for central banks to intervene when necessary to stabilize the currency. By providing timely and accurate predictions, the GARCH model enables monetary authorities to make informed decisions about policy interventions, such as adjusting interest rates or engaging in foreign exchange market operations. These interventions, in turn, help maintain economic stability and safeguard investor confidence in the country's financial markets.

Understanding and managing exchange rate volatility is crucial for market participants, especially multinational corporations and foreign investors. High and persistent volatility can introduce uncertainty into financial and business planning, particularly for companies engaged in international trade or exposed to multiple currencies. Using the GARCH model's predictions, these entities can implement risk management strategies, such as hedging with currency forwards or options, to mitigate the impact of adverse currency movements. These measures are essential to protecting profit margins and reducing the financial risks of volatile exchange rates.

Furthermore, this study's findings underscore the broader policy implications for Indonesia's fiscal and monetary strategies. As a developing economy highly reliant on international trade and foreign investment, Indonesia must carefully manage external shocks that could lead to significant exchange rate fluctuations. For instance, changes in global oil prices or shifts in U.S. monetary policy can directly impact the value of the Rupiah. By integrating GARCH-based volatility forecasts into policy frameworks, Indonesia's government and central bank can better coordinate fiscal and monetary responses to such external pressures, reducing the negative effects of exchange rate movements on the domestic economy.

Future research could expand on this study by incorporating additional macroeconomic variables, such as inflation, interest rates, GDP growth, and commodity prices, into the GARCH model. A multivariate GARCH (MGARCH) approach would offer a more comprehensive view of the factors influencing exchange rate volatility, allowing for deeper insights into how domestic and global economic conditions affect currency dynamics. Moreover, integrating traditional econometric models like GARCH with advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks or Random Forest algorithms, could further enhance the predictive accuracy of volatility models.

In conclusion, the GARCH model provides significant advantages for forecasting the volatility of the Rupiah against the USD, offering valuable insights for policymakers and market participants alike. While this study contributes to understanding exchange rate volatility, future research can build upon these findings by incorporating additional macroeconomic variables and exploring innovative methodologies further to improve the accuracy and applicability of volatility predictions. This will ultimately benefit decision-makers in navigating the complexities of global financial markets.

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