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Volatility Modelling and Forecasting of Indonesia-USA Currency Using Constant Conditional Multivariate GARCH

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Abstract: This paper estimated and forecasted the volatility of USD/IDR exchange rate using Constant Conditional Multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and ARIMA (Autoregressive Moving Average) as the methods. The objective of this study is to comprehend and to execute a projection of the currency of Indonesia and Philippines while understanding the rapid movement of the variables (volatilility). The variables used are USD/IDR, Jakarta Stock Exchange Composite Index (JCI), World Oil Price, and Nominal Broad U.S. Dollar Index. The data was daily, taken from World Bank, Federal Reserve Economic Data, and Indonesian Stock Exchange during 2006-2025. The result showed that there was short term autoregressive moving average dynamics in USD/IDR return, through Mean Equation. The GARCH model showed high persistence of volatility and the shocks showed indication of long-lasting in term of duration. Persistent volatility implied that USD/IDR was sensitive to external shocks. The result also confirmed that the volatility is time-varying, meaning the fluctuations tend to cluster into specific downturn or upturn movement. The method used in this study did not consider about different period in volatility (leverage effect) as it used symmetric volatility as assumption.

Keywords: GARCH, Exchange Rate, Volatility, Modelling

Introduction

It is essential to look into volatility modelling to forecast exchange rate movement in a country. In the midst of challenges happening in economic world dynamics nowadays, forecasting exchange rate volatility remains pertinent to construct a model with which economists can investigate the direction of exchange rate will be going (Makore & Chikutuma, 2025). While monetary sector is not represented solely by

exchange rates between countries, emerging countries around the world experienced persistent volatile exchange rate (Umoru et al, 2023)(Dinga et al, 2023). It is known that exchange rate movement tend to vehemently show rapid fluctuations, while it still remains as a core variable that occupies the centre connection between monetary performance of a country and international transactions between countries (Olamide et al, 2022).

Previous studies across the globe have been conducted to investigate the volatility in exchange rate. Whether it is to construct a model (Almisshal & Emir, 2021) (Jabeen & Khan) (Zhang et al., 2024) or to forecast future volatility (Sabkha et al, 2021) (Trabelsi & Bahloul, 2022). Constant conditional multivariate GARCH have been used in researches about exchange rate volatility model (Mușetescu et al, 2022) (Wang et al, 2022). Furthermore, studies about monetary spillover or macroeconomic relationship between USA and Indonesia have been done with focusing on exchange rate as one of its variables (Suwondo et al, 2023) (Suwondo et al, 2023) (Suwondo et al, 2025). An observation into monetary variables between USA and Indonesia using USD/IDR and stock market price have been conducted before, but not specifically including World Oil Price or Nominal US Broad Index.

Exchange rate volatility tend to signal noteworthy events that influence respective economies (Dukundane, 2023). Modelling exchange rate volatility is tricky when the researcher is not taking asymmetric assumption into the model. It was discovered that observing real-life situations, in which all monetary variables were derived from, was challenging to do because of the heterogeneity which happened because the variance (or spread) of the model's residuals is not constant across all values of the independent variable (Hasnanda, 2020) (A.K. et al, 2023). Therefore, GARCH was selected as a method of analysis because of its asymmetric assumption use and ability to capture volatility better than ARMA method.

Monetary variables, such as exchange rate, are known to exhibit trend patterns which were the fundamentals of observing estimation and forecasting (Dukundane, 2023). In times of volatility observation particularly for heavily fluctuating monetary variables, many researches were common to indulge in ARCH or GARCH methods (Olamide et al, 2022) (Dinga et al, 2023) (Ezzebsa et al, 2023). Persistency of variations in exchange rate volatility were deemed as attrative in terms of topics researched by researchers. In many of those researches, varieties of ARCH and GARCH were implemented (Sabkha et al, 2021) (Sharma et al, 2021) (Khoury et al, 2024) (Makore & Chikutuma, 2025). Another method was used such as Panel Data Analysis and VAR/VECM (Olamide et al, 2022) (Suwondo et al, 2023). Alas, the reasoning behind all those different methods of analysis was to chose the best approach to investigate the

volatility of exchange rate. In Figure 1 below it was shown a comparison between arithmetic and logarithmic graph of daily exchange in USD/IDR.

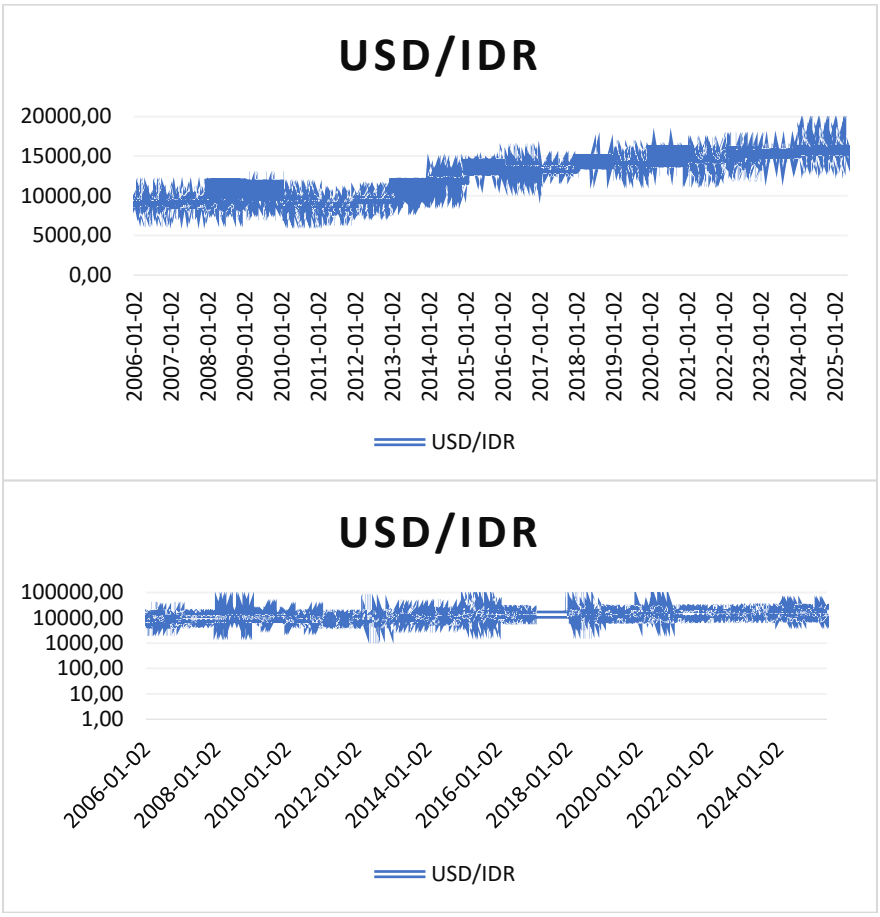

Figure 1. Arithmetic and Logarithmic Graph Comparison of USD/IDR

Figure 1 provided comparison of volatility performance of USD/IDR exchange rate. When we're investigating the data using arithmetic graph, it would compile decades long of data and plaster it into line trend graph such as shown. Given the characteristics of the variable used here, the fluctuations were spanning wide between two polar extremes, thus the volatility that was displayed were clustering in each clump. In previous Indonesian economic crises going way back in 1998 and 2008 as well as economic downturn in 2016 and 2020, USD/IDR exchange rate took a major hit and the nominal value was so large in number compared to the appreciative ones (Suwondo, Pratama & Qodri, 2025a) (Suwondo, Pratama, Lutfi & et al, 2025). When data that are spanning through decades and have tendency of high volatility over time with very distinguish trend of upturns and downturns, we can use arithmetic graph to have a better look into each value of the data.

The same thing can not be said to when we use logarithmic graph for observing exchange rate volatility over time, because rather than displaying the nominal value of the data, it showed percentage as the Y axis (Ezzebsa et al, 2023 (Moody' S Analytics & Perron). Logarithmic graph is commonly used in order to observe the volatility of the data regardless the nominal value of it, particularly for wide range timespan and extreme values. It was shown in Figure 1 the percentage changes of USD/IDR exchange rate were presented more clearly and the trend was visualized as lines that were showing the upturns and downturns without being swayed by the nominal values extremity.
The equation for the exchange rate using logarithmic scale that was displayed in Figure 1 could be seen below, adapted from Epaphra (2017):

$$r_t = \log\left(\frac{x_t}{x_{t-1}}\right) = \log(x_t) - \log(x_{t-1})$$

While r_t stands for the log price relative at time t, and variable x_t stands for exchange rate during time t. As for as x_{t-1} , it stands for exchange rate at a periode before time t.

Modelling exchange rate volatility was considered challenging for academic researchers. The implications of the volatility were not only revolving around financial stability of the country, but also around other macroeconomic variables (Abdalla, 2012; Almisshal, 2021; Umoru, Effiong, Ugbaka, et al., 2023). In theory, exchange rates do indeed move based on supply and demand, but the movement also reflected the economic policy of a country (Umoru, Akpoviroro et al, 2023). This also apply for economic policy from foreign country, moreso the counterpart nation of the exchange rate (such as, USD/IDR in this paper) Thus, it strengthens the condition that exchange rate is influenced heavily by macroeconomic changes.

A number of studies have investigated exchange rate volatility using GARCH models, particularly when ones intended to conduct volatility modelling (Abd Rahman et al, 2023) (A.K. et al, 2023) (Ezzebsa et al, 2023). Well known conducts around the exchange rate volatility estimation were using autoregressive conditional heteroskedasticity (ARCH) model, which garchfurthermore advanced into generalized autogregressive conditional heteroskedasticity (GARCH) model (Epaphra, 2017). These methods were chosen to account for characteristics of exchange rate volatility, i.e., the dynamics of conditional heteroskedasticity in this particular maroeconomic indicator. In highly fluctuating variable such as exchange rate, heteroskedasticity often occurred. GARCH method was applied in order to combat this inconstant variance distribution (Eniayewu et al, 2024).

The GARCH process was first established by Engle (Chen, 2023) after it was recognized the difference between conditional and unconditional variance in variables.

It was widely accepted by academics that autoregressive moving average (ARMA) method was applied to estimate data that are highly fluctuative, which was mostly time-series data. Of course, financial and monetary data were falling into this category, thus the previous researches around monetary variables were using a lot of autoregressive as well as moving average methods. When conducting estimation using GARCH method, the log in the model were commonly long particularly for conditional variance equations, to avoid problems with negative variance (Ochoa & Sosa, 2021) (Abd Rahman et al, 2023). In short, GARCH can be used if ARMA can no longer be used, because there was heteroscedasticity and we could not use ARMA if the data were not homoskedasticity.

The significance of this study is to contribute to the scope of research on modelling exchange rate volatility and conduct a forecast of future USD/IDR exchange rate. It comes into understanding that by studying the volatility of exchange rate and constructing a model while conducting a forecast, this paper further contributes to the depth of the topic, especially regarding USA-Indonesia macroeconomic sensitivity. Another contribution of this research is providing additional analysis to the government as consideration when implementing policies regarding Indonesian exchange rate, while putting World Oil Price and Nominal US Broad Index into factors.

Research Method

Model Specification

The main objective of this paper is to estimate and create volatility modelling for exchange rate (USD/IDR) using GARCH model. This paper also conducted a forecast for USD/IDR performance in the future. Because the high volatility nature as well as the occurance of heteroskedasticity of the data, this paper could not conduct estimation using ARMA method, but opted for GARCH instead. Thus, this paper estimated the data not only by constructing Mean Equation for model specification, but also Variance Equation. It is essential to include Variance Equation to the estimation because of the inconstant distribution of the variance for USD/IDR.

The data used in this paper are USD/IDR, Jakarta Stock Exchange Composite Index (JCI), World Oil Price, and Nominal Broad U.S. Dollar Index. The data taken was daily, sourced from World Bank, Federal Reserve Economic Data, and Indonesian Stock Exchange during 2006-2025. The total number of data used in this research was 5.049 n or units.

The Mean Equation (dependent variable= USD/IDR):

$$Y_t = \propto + \beta \sum_{i=1}^{n=5.049} [w_{t-i} + x_{t-i} + z_{t-i}] + \varepsilon_t \qquad (1)$$

The n was 5,049 as addressed above, and Y_t was the dependent variable, which was USD/IDR, while w_t was IHSG or Jakarta Stock Exchange Composite Index (JCI), x_t was World Oil Price, z_t was Nominal Broad U.S. Dollar Index (the trade weighted of USD, which is the value of the United States dollar relative to other world currency, and in this case Indonesian IDR). The last variable which was ε_t stands for error/disturbance term, or white noise occurring during the estimation.

While The Variance Equation was as following:

$$\sigma_t^2 = c + \beta_1 \sigma_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 + \vartheta_t \quad (2)$$

The variable $\beta_1 \sigma_{t-1}^2$ was for GARCH model, and the variable $\gamma_1 \varepsilon_{t-1}^2$ was for RESID $(-1)^2$ or residual from the estimation. The estimation conducted in this paper was not only for assessing autoregressive moving average equation for time-series data, but also for estimating the inconstant residual or variance of the data, which was why Variance Equation was included.

Estimation

Despite difference methods employed by previous researches regarding volatility modelling and performance forecasting of the exchange rate (Ochoa & Sosa, 2021; Trabelsi & Bahloul, 2022; Dinga et al., 2023b; KILIÇ et al., 2023), this paper focused on GARCH method in conducting the estimation. This method was chosen precisely because it enhances the accuracy of the volatility forecast by putting errors from previous prediction into account. The inconstant residual or variance of the data was also accommodated by this method, because common autoregressive moving average could not assess abnormally distributed variance of the error term because of the misleading standard errors for coefficients and poor model performance if it continues on. In order to handle this matter, it is necessary to conduct transformation of time-series data, using logarithmic estimation such as GARCH.

The estimation steps in this study were conducted by running Unit Root Test (Augmented Dickey Fuller), while it consciously went for 1st Difference, not on Level or 2nd Difference. It became necessary because it is required in GARCH models to possess first-differenced (stationary) data because non-stationary level data are intended to result in unreliable parameter estimates and a biased model, especially if the data exhibits trends or structural breaks in between the fluctuations (Makore & Chikutuma, 2025). Afterwards, correlogram test was required to determine the order (p, q), with p means the autoregressive (AR) order, and q means moving average (MA) component order.

After the order was established, the next step that was necessary to conduct is Heteroskedasticity Residual Diagnostic Test, with hypothesis H0=homoskedasticity and

H1=heteroskedasticity. The test was needed to run so that H1 is accepted and H0 is rejected, so heteroskedasticity occurs. GARCH can only be used if ARIMA can no longer be chosen, because there is heteroskedasticity. After this, the next step would be determining the Determining the Length of the Conditional Variance, which is the basis for conducting GARCH analysis (Lim et al., 2023). And the last step was to run GARCH estimation, and conducting forecast for USD/IDR and for the variance using Static Forecast while incorporating GARCH into the command.

Result and Discussion

Before continuing with GARCH estimation method, it was required to run Unit Root Test Augmented Dickey-Fuller (ADF) beforehand, in order to ensure the stationarity of the data. The result was shown in Table 1. It could be observed that all variables were not stationary in Level, rather they were all stationary in First Difference, fulfilling the first criteria to be able to continue using GARCH method. The significance level that was used in this test was 5%.

Table 1. ADF Unit Root Test Result

Variable	ADF Statistics Level	ADF Statistics First Difference
Y (USD/IDR)	0.8494	*0.0000
W (JCI Index)	0.0961	*0.0001
X (Global Oil Price)	0.0157	*0.0000
Z (USD National Broad Index)	0.8680	*0.0001

After confirming that the data were all stationary, the authors conducted Correlogram Test to determine the order. The orders used here are P & Q, where p = order of the autoregressive component (AR), while q = order of the moving average component (MA). The significance level that was being used was 5%. The test result was presented in Table 2 below, which displayed the probability of both AR(1) and MA(1) to be significant in less than 5% level. From this result we can conclude that the ARIMA that would be used in this study for Mean Equation was in the order of (1, 1, 1) with AR(1) and MA(1).

Table 2. Correlogram Test Result

Variable	Coefficient	Std. Error	t-Statistics	Prob.
AR(1)	-0.462016	0.063482	-7.277913	*0.0000
MA(1)	0.603368	0.057083	10.56997	*0.0000

After choosing the order for Mean Equation to be (1, 1, 1) using AR(1) and MA(1), the step afterwards would be running hypothesis diagnostic for Heteroskedasticity using Heteroskedasticity Residual Diagnostic Test. The goal was to reject H0, thus it is requisite to determine what are the H0 and H1 would be, which were as follow: H0= homoskedasticity, and H1=heteroskedasticity. When we reject H0 and accept H1, that would mean that there is heteroskedasticity in the data, which then result in the ability of this study using GARCH as a method of analysis. The result was shown in Table 3, which revealed that the probability for both F-Statistic and Obs*R-squared (Chi-Square) was significant in less than 5% level. Seeing these results, it was concluded that this study cannot use ARIMA and must use GARCH.

The next step was to determine the length of Conditional Variance, required to do for Variance Equation. It is the basis for performing GARCH, because doing so would present us with Variance Conditional representative, meaning it is a necessary step before establishing the order for Variance Equation analysis. After receiving the result for r1 (residual series) that was shown in Figure 2 below, then it is required to square the result and make it into r2. It is imperative to note that ARIMA analysis is an analysis with a mean system, while GARCH with a system focused on Conditional Variance. The order that was used for GARCH was p,q (1,1).

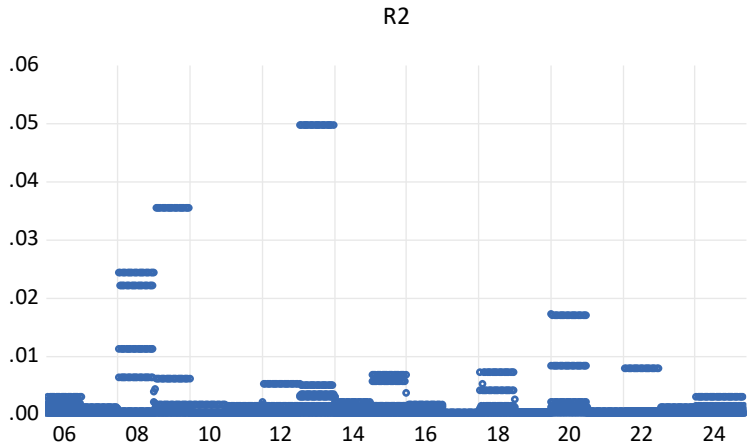

Figure 2. Variance Conditional Test Result

The most important step to perform in this study is GARCH method. The result was displayed in Table 3 and Table 4, for GARCH analysis and Residual Diagnostic (ARCH LM Test) result respectively. From GARCH result, it could be concluded that the probability for both AR(1) and MA(1) were significant at the level of 1%, which means that the past square residual terms can significantly affect the volatility of USD/IDR.

Table 3. GARCH Result

Variable	Probability	RESID(-1)^2	GARCH(-1)
AR(1)	0.0000	0.0000	0.0000
MA(1)	0.0000	0.0000	0.0000

Meanwhile, Table 4 presented ARCH LM Test Result, which was the Residual Diagnostic Test ran in order to figure out whether there is still heteroskedasticity occurring in the data or not. It could be seen from the value 0.0895 of F-Probability and 0.0895 of Chi-Square that both of them did not meet the 5% significance level, thus failing to reject H0. Therefore, the model is homoskedastic and no longer heteroskedastic.

Table 4. ARCH LM Test Result

Variable	F-Statistics (ARCH LM)	Chi-Square (ARCH LM)
WGT_RESID^2(-1)	0.0895	0.0895

The forecasting for the future performance of USD/IDR was displayed in Figure 3 the Static Forecast for USD/IDR. From the picture shown, it was stated that the Root Mean Squared Error was 0.034189, which meant that the accuracy for this forecast is reasonable. Low number for this value is better, because it represented the mean for errors in the forecasting. The same thing was shown in Mean Absolute Error value, because it also showed low number in 0.021670, almost the same with Root Mean Squared Error. This revelation confirmed previous error forecasting estimation. The Inequality Coefficient, which consisted of Bias Proportion, Variance Proportion, and Covariance Proportion showed a total estimation value of 0.001820. It was a number closer to 0, and the closer the number of this value to 0, the better it would be for the result, because it proposed that there was actually a minimal bias for the forecasting result.

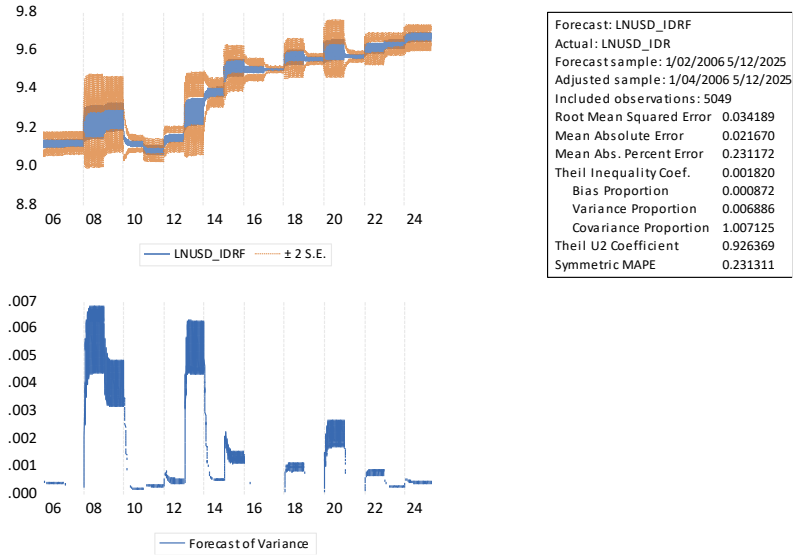

Figure 3. Forecasting Result

Verification Hypotheses and Previous Research Relevance

As previously stated in former paragraphs, this study indulged in 2 equations for the estimation model as well as the forecasting test, which were: Mean Equation and Variance Equation. Mean Equation explained the return of the data fluctuations, whereas the Variance Equation explained more about the volatility shocks. JCI Index was among those to explain the return of data fluctuations, while Global Oil Price and US National represented the volatility shocks. From both AR(1) and MA(1) results from Mean Equation, we could derive understanding that it was indicated that there was persistence in return. It was shown in p-value of both result that showed number very close (if not totally) to 0, which were both showed to be 0.0000. This would mean that past value of the variables affected positively the current value for the variables. Whereas the value for MA(1) showed that there was rapid adjustments to shocks, meaning that the volatility of USD/IDR was, although changing very actively over time, but it adjusted itself well to its equilibrium value. These results implied that although the dynamics of USD/IDR fluctuations was high, but it was relatively short-term because the ability for USD/IDR to go back to its equilibrium value.

Conclusion

Exchange rate between IDR and USD remained as one of the most volatile macroeconomic indicators over the years. This study discovered that the volatility of the Indonesia-United States (USD/IDR) exchange rate exhibited repeated ups and downs, with clustering of both appreciations and depreciations. However, despite these massive increases and decreases, there was a dynamic autoregressive movement in the short term. Furthermore, volatility persistence was found, driven by sensitivity to external economic shocks. Moreover, although sensitivity to external economic shocks was found in the USD/IDR, historical data on the variable determined its future value. Furthermore, the USD/IDR value adjusted after being impacted by economic shocks, allowing the variable to return to its equilibrium point. This indicates that although the USD/IDR movement exhibits a high dynamic signal, policies implemented by regulators (the government and the central bank) can accelerate the USD/IDR's return to its initial equilibrium value (before the shock).

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