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A GARCH MODEL TO FORECASTING VOLATILITY OF OIL AND GAS EXPORT IN INDONESIA

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ABSTRACT

This research aims to analyze the dynamics of oil and gas exports in Indonesia during the period from 2012 to 2022 using the GARCH approach for forecasting volatility. The data utilized in this study encompass the monthly published volumes of Indonesia's oil and gas exports, sourced from the Indonesian Central Statistics Agency's website. The analysis involves a substantial amount of data, comprising 132 monthly time series spanning a significant timeframe. The findings indicate that the most suitable model for predicting oil and gas volumes is the GARCH (1,1) model. The GARCH approach is employed to model the volatility within the data of oil and gas exports. The results reveal the utilization of information criteria, including Akaike (14.73), Bayes (14.86), Shibata (14.73), and Hannan-Quinn (14.79). Moreover, the forecast analysis for the next ten periods depicts a consistent upward trend. Generally, these forecast results suggest that while the mean values of the data remain relatively stable, the volatility levels are anticipated to increase over the forthcoming periods. The implications of this research are crucial within the context of economic and international trade, as the volatility in oil and gas exports can significantly impact national economic policies and corporate decisions.

Keywords : Oil And Gas, GARCH, Export, Forecasting

I. INTRODUCTION

The global oil and gas industry plays a pivotal role in the economies of resource-rich countries like Indonesia. Indonesia, as one of the world's largest exporters of oil and natural gas [1], [2], heavily relies on the revenue generated from these commodities to support its economic growth and development. However, the volatility in global oil and gas prices poses significant challenges to the stability and predictability of export earnings [3]. Understanding and effectively managing this volatility is crucial for policymakers, investors, and industry stakeholders.

The volatility inherent in the oil and gas industry presents various challenges for policymakers, investors, and market participants. Forecasting the volatility of oil and gas exports is crucial for making informed decisions, managing risks, and developing effective strategies [4]. To illustrate the significance of volatility forecasting in Indonesia's oil and gas industry, consider the period between 2015 and 2016 when global oil prices experienced a sharp decline, resulting in substantial economic challenges for oil-exporting countries [5]. During this period, Indonesia faced critical policy dilemmas, including the need to adapt to the changing market dynamics, reassess the national budget, and address potential economic vulnerabilities.

In mathematics, several forecasting models have been developed and they focus on the projection of future values from past data. These models are widely used in different segments including economics [6]–[8], finance [7], [9], weather predicting [10], [11], supply chain management [12], [13] and so on. It is crucial here to remember that they employ mathematical and statistical tools in analyzing data for patterns, trends, as well as relations. By employing advanced forecasting techniques such as the GARCH approach, policymakers could have anticipated the impending volatility and formulated proactive strategies to mitigate the adverse effects of market fluctuations. This case underscores the importance of accurate and timely volatility forecasts in facilitating effective economic management and policy formulation in Indonesia's oil and gas sector.

Over the years, researchers and analysts have employed a variety of econometric models to study and predict the volatility of oil and gas prices [14]–[16]. The use of GARCH model is vital because recent methods of forecasting have some weaknesses that can be covered by GARCH model. Smoothing methodologies like simple moving average and exponential moving average are generally used for volatility forecasting [17]. The main disadvantage of these methods is their simplicity and interpretability, and the most serious one is that they are incapable of capturing complex interactions in variance of financial data. These methods work on the assumption of equal variability in the data [18] and this is far from the truth especially with the energy market volatility. Several other techniques, including ARIMA and all its modifications, can also be used for time series forecasting [19]. In addition, a significant drawback of applying ARIMA models is the lack of consideration of the variance of the series where it is sometimes adequate to consider only the mean of the series. This is a major drawback when it comes to the prediction of fluctuation in export of oil and gas especially when the volatility is large due to various factors such as economic or geopolitical instabilities.

One of the widely recognized and commonly used models in this context is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models have gained popularity due to their effectiveness in capturing the time-varying nature of volatility in financial and commodity markets. This feature allows for more precise assessments of risk and more accurate forecasts of future price movements.

A research proposed a two-regime switching GARCH-MIDAS model to explore the connections between oil price volatility and macroeconomic fundamentals. The research identified evidence indicating that structural breaks lead to a higher level of persistence in GARCH-implied volatility. Notably, the two-regime GARCH-MIDAS models demonstrated a significant improvement in forecasting oil volatility compared to their single-regime counterparts when assessed out-of-sample [20]–[22]. Other research focused on addressing the volatility and heteroscedasticity variance in Crude Oil Price (COP) data using the GARCH model. Daily COP data spanning from 2009 to 2018 were analyzed to find the best-fitted model for forecasting daily COP movements. The research identified that the AR (1) – GARCH (1,1) model yielded the most accurate results [23].

This research focuses on analyzing the dynamics of Indonesia's oil and gas export volatility over the period from 2012 to 2022, employing the GARCH approach. By utilizing the GARCH approach, this research seeks to provide accurate and reliable predictions of future volatility[24], [25], enabling stakeholders to proactively respond to market fluctuations and make well-informed decisions. A study reported that when employing GARCH models, it is crucial to estimate their parameters accurately to make reliable volatility forecasts [26].

The novelty of this research lies in the application of the GARCH methodology to forecast volatility in Indonesia's oil and gas exports. While prior studies have explored various forecasting techniques in the energy sector, the utilization of GARCH specifically for analyzing Indonesia's oil and gas export volatility represents a novel contribution. By focusing on this specific context, the research aims to fill the gap in the existing literature by providing a comprehensive understanding of the intricate dynamics of Indonesia's energy market and the implications of volatility for the national economy.

Moreover, this research contributes to the field of energy economics by offering a robust and reliable framework for predicting future volatility trends. The utilization of the GARCH approach allows for a more accurate assessment of risk exposure and the formulation of effective risk management strategies. The findings of this study have the potential to assist policymakers, investors, and industry stakeholders in making informed decisions, enhancing the resilience of the Indonesian energy sector, and fostering sustainable development in the face of fluctuating global energy markets. By highlighting the significance of volatility forecasting, this research contributes to the advancement of knowledge in energy economics and provides valuable insights for effective policy formulation and strategic planning in the oil and gas industry.

II. METHODS

2.1. Data

The data used for the forecasting analysis in this study is secondary data on the volume of Indonesia's oil and gas exports for the period 2012 to 2022. These data are monthly data from BPS published on its website. There are 132 series of data used in this analysis. Figure 1 shows the data used in the analysis of the forecast of the volume of Indonesian oil and gas exports (in thousands of tons).

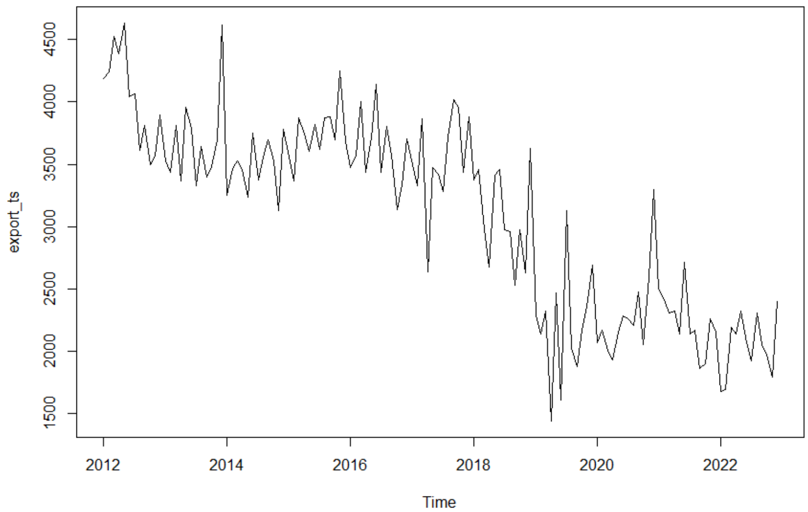


Figure 1 : Plot data series

2.2. GARCH Modeling

To forecast volatility, this research employs the GARCH approach, a widely recognized method for modeling and predicting time-varying volatility in financial and economic data. The GARCH model enables the assessment of conditional variance based on past information, incorporating both autoregressive and moving average components to capture the volatility patterns accurately. This research uses the GARCH model, in which serves as a fundamental framework for capturing time-varying volatility in financial and economic time series data, allowing for the modeling of complex dynamics and the prediction of future volatility patterns. The GARCH(*p*,*q*) model can be represented by the following mathematical formulas [27]:

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

Where $i = 0,1, \dots, p$ and $j = 1, \dots, q$. The mean equation μ_t, which represent the mean at time t is defined by $\mu_t = E(r_t)$. If $\omega > 0$ and the coefficients α_i and β_j are all non-negative then $\sigma_t^2 > 0$ [27]. σ_t^2 represents the conditional variance at time t, ω is the constant term or the intercept, in which representing the long-term average variance. α_i represents the coefficient for the lagged squared residual term (ARCH term), in which capturing the impact of past forecast errors on the current volatility. ε_{t-i}^2 is the lagged squared residual at time *t-i*. β_j is the coefficient for the lagged conditional variance term (GARCH term), in which representing the impact of past conditional variance on the current volatility. σ_{t-j}^2 is the lagged conditional variance at time *t-j*. Then the GARCH (1,1) model can be written as follows [27]:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ + \beta_1 \sigma_{t-1}^2$$

Using merely three parameters in the conditional variance equation is sufficient to achieve a well-fitted model [27].

2.3. Model Estimation

The GARCH model parameters, including mean, autoregressive (AR), moving average (MA), and omega, are estimated using appropriate statistical software. The estimation process involves fitting the GARCH model to the dataset, allowing for the identification of the optimal model specification that best captures the volatility dynamics within Indonesia's oil and gas exports.

2.4. Model Evaluation

The performance of the GARCH model is evaluated based on various criteria, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), the Shibata Criterion, and Hanan-Quinn Criterion. This evaluation process enables the comparison of alternative model specifications and the selection of the most appropriate GARCH model that effectively forecasts volatility in Indonesia's oil and gas exports.

III. RESULTS AND DISSCUSSION

3.1. Selection of The Best Model

The selection of the best model is based on information criteria such as Akaike, Bayes, Shibata, and Hannan-Quinn. The lower the criterion value, the better the model. The information criteria include Akaike, Bayes, Shibata, and Hannan-Quinn. This information is used to compare the model with other models. The lower the information criterion value, the better the model. Table 1 demonstrates several comparisons of the mean models as the basis for determining the optimal GARCH model in analyzing the prediction of oil and gas exports in Indonesia during the period from 2012 to 2022.

Table 1 : Information Criteria

Model	**Criteria**			
	Akaike	**Bayes**	**Shibata**	**Hannan-Quinn**
ARFIMA(1,0,0)	15.12	15.23	15.12	15.16
ARFIMA(0,0,1)	15.64	15.75	15.64	15.69
ARFIMA(1,0,1)	14.73	14.86	14.73	14.78
ARFIMA(2,0,1)	14.73	14.88	14.72	14.79
ARFIMA(1,0,2)	14.74	14.89	14.74	14.80

Table 2 presents the analysis results related to the optimal parameters of the offered model. This section provides parameter estimations from the estimated GARCH models. The estimated parameters include mean (mu), autoregression AR(1), moving average MA(1), omega, alpha1 (alpha1), and beta1 (beta1). Each parameter is accompanied by estimations, standard errors, the value of t-statistics, and the p-value for the null hypothesis test (insignificant). This comprehensive analysis offers insights into the significance of the estimated parameters and their respective impacts on the overall model.

Table 2 : Optimal Parameters

Model		mu	AR(1)	AR(2)	MA(1)	MA(2)	omega	alpha1	beta1
ARFIMA(1,0,0)	Estimate	3389.27	0.87				624.49	0.11	0.88
	Std.Error	325.35	0.07				5846.20	0.10	0.09
	t-value	10.42	12.19				0.11	1.15	10.25
	p-value	0.00	0.00				0.91	0.25	0.00
ARFIMA(0,0,1)	Estimate	3427.59			0.47		613.91	0.11	0.89
	Std.Error	92.16			0.07		4449.00	0.03	0.04
	t-value	37.19			6.42		0.14	3.35	20.47
	p-value	0.00			0.00		0.89	0.00	0.00
ARFIMA(1,0,1)	Estimate	4237.94	1.00		-0.71		827.18	0.06	0.94
	Std.Error	260.61	0.01		0.07		2790.30	0.05	4.27
	t-value	16.26	122.57		-10.78		0.30	1.20	21.95
	p-value	0.00	0.00		0.00		0.77	0.23	0.00
ARFIMA(2,0,1)	Estimate	429.25	0.87	0.13	-0.65		700.09	0.00	1.00
	Std.Error	214.84	0.12	0.12	0.10		2037.80	0.01	0.01
	t-value	19.98	7.15	1.10	-6.86		0.34	0.00	92.34
	p-value	0.00	0.00	0.27	0.00		0.73	1.00	0.00
ARFIMA(1,0,2)	Estimate	42.70	1.00		-0.77	0.08	690.49	0.05	0.95
	Std.Error	263.28	0.01		0.09	0.09	2640.70	0.05	0.05
	t-value	16.22	115.64		-8.56	0.94	0.26	1.03	20.61
	p-value	0.00	0.00		0.00	0.35	0.79	0.30	0.00

The research analysis distinctly reveals that across all criteria, the most suitable model to be employed is ARFIMA (1,0,1), as nearly all the criteria present the lowest figures compared to other models. From Table 1, the analysis highlights that all criteria exhibit closely similar values (Akaike=14.73; Bayes=14.86; Shibata=14.73, and Hannan-Quinn=14.79). The ARFIMA (1,0,1) model comprises one autoregressive (AR) component and one moving average (MA) component in the conditional variance. This model indicates a mean model with first-order autoregression (AR) and first-order moving average (MA).

3.2. The Results of GARCH (1,1) on Oil and Gas Export Predictions

Based on identification of the best model selection, the optimal GARCH model suitable for the analysis of oil and gas export predictions in Indonesia during the period from 2012 to 2022 is the GARCH (1,1) model. Table 3 demonstrates the analysis results using the GARCH (1,1) model.

Table 3 : Optimal Parameters GARCH (1,1)

Parameters	Optimal Parameters				Robust Standard Errors			
	Estimate	Std. Error	t-value	p-value	Estimate	Std. Error	t-value	p-value
mu	4237,94	260,61	16,26	0,00	4237,94	118,98	35,62	0,00
AR(1)	1,00	0,01	122,57	0,00	1,00	0,01	146,35	0,00
MA(1)	-0,71	0,07	-10,78	0,00	-0,71	0,06	-12,29	0,00
omega	827,18	2790,30	0,30	0,77	827,18	2893,10	0,29	0,77
alpha1	0,06	0,05	1,20	0,23	0,06	0,10	0,61	0,54
beta1	0,94	4,27	21,95	0,00	0,94	0,07	14,04	0,00

From Table 3, the research findings provide crucial insights into the analysis of the oil and gas export data. The key findings from the study are detailed as follows. The mean value (*mu*) of the oil and gas export data is estimated to be 4237.94. This suggests that, on average, the oil and gas exports tend to hover around this value. Understanding the mean value can provide an initial indication of the performance or general trend in the oil and gas export sector. The autoregressive parameter (AR(1)) value from the GARCH model is exceptionally high, at 1.00. This indicates a strong dependency between sequential values in the oil and gas export data. This dependency may indicate repetitive patterns or trends in the data that can be used to forecast future movements in the oil and gas export sector. The first moving average parameter (MA(1)) from the GARCH model has a value of -0.71. This negative value suggests the presence of a moving average effect in the data. This information provides an understanding of the influence of the average movement on sequential values in the oil and gas export data. The constant (bias) from the GARCH model, which measures constant volatility in the data, is valued at 827.18. This constant value indicates the base level of volatility that can serve as a reference for understanding general fluctuations in the oil and gas export data. The alpha parameter (α) from the GARCH model is estimated at 0.06. This value measures the impact of past volatility on current volatility. This information can help in understanding the resilience of fluctuations and volatility patterns within the oil and gas export data. The beta parameter (β) from the GARCH model is estimated to be 0.94. This value measures the extent to which the volatility of the mean value affects current volatility. Understanding this parameter can provide insights into how changes in the mean value can influence fluctuations in the oil and gas export data. These findings establish a robust foundation for comprehending the characteristics, patterns, and movements within the oil and gas export data. Stakeholders can utilize this information to make more informed strategic decisions concerning investments, risk management, and the development of the industry sector.

From Table 3, the estimation results with robust standard errors are evident. This section highlights parameter estimates that are robust against heteroscedasticity. Robust standard errors can provide more reliable estimates if the basic assumptions of the model are not met. These results provide an overview of the estimated parameters in the GARCH model for oil and gas export data in Indonesia. These parameters will be utilized to formulate volatility models and forecast future volatility. It is noteworthy that these parameters have t-values and p-values that aid in testing the statistical significance of each parameter in the model. Subsequently, the analysis results indicate that the majority of the parameters have high t-statistics and p-values approaching zero, indicating their statistical significance.

Furthermore, the analysis results provide the log-likelihood value of the model as -966.22. This log-likelihood value serves as a crucial metric used in the model estimation process. Additionally, this study employs the weighted Ljung-Box Test and Weighted ARCH LM Tests (Autoregressive Conditional Heteroskedasticity Lagrange Multiplier Tests) to test the basic assumptions of the model and assess whether the estimated GARCH model fits the utilized data. Table 2 illustrates the outcomes of the tests for the basic assumptions of the model.

Table 4 : Basic Assumptions

	Weighted Ljung-Box Test on Standardized Residuals		Weighted Ljung-Box Test on Standardized Squared Residuals	
	statistic	p-value	statistic	p-value
Lag[1]	1.011	0.315	0.728	0.394
Lag[2*(p+q)+(p+q)-1][5]	1.806	0.984	1.262	0.798
Lag[4*(p+q)+(p+q)-1][9]	5.365	0.374	1.904	0.916

From Table 4, the results of the Weighted Ljung-Box Test on Standardized Residuals are used to examine whether there is any serial correlation in the residuals generated by the GARCH model. This test assesses multiple lags to determine if there is any significant correlation. High p-values (e.g., > 0.05) indicate that there is insufficient evidence to reject the null hypothesis (H_0: No serial correlation), implying that the residuals do not exhibit significant serial correlation. On the other hand, the results of the Weighted Ljung-Box Test on Standardized Squared Residuals are used to test whether there is any serial correlation in the squared values of the residuals generated by the GARCH model. High p-values suggest that there is insufficient evidence to reject the null hypothesis, indicating that the squared residuals do not display significant serial correlation.

Furthermore, the results of Weighted ARCH LM Tests, in which used to examine the presence of autoregressive conditional heteroscedasticity (ARCH) in the residuals of the GARCH model, are presented in Table 5.

Table 5 : Weighted ARCH LM Tests

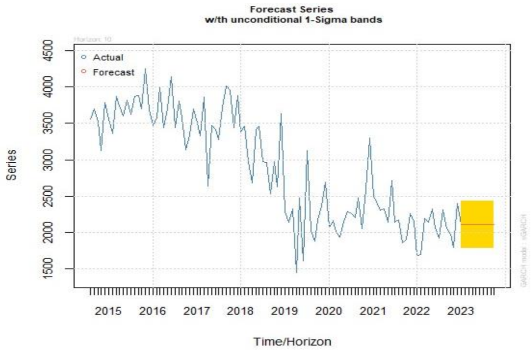
	Statistic	Shape	Scale	p-value
ARCH Lag[3]	0.009	0.500	2.000	0.927
ARCH Lag[5]	0.520	1.440	1.667	0.878
ARCH Lag[7]	0.777	2.315	1.543	0.947

According to Table 5, the statistic value represents the result of the test, while the P-Value signifies the statistical significance. A high P-Value (greater than 0.05) indicates that there is insufficient evidence to reject the null hypothesis, suggesting the absence of significant autoregressive heteroscedasticity patterns in the GARCH model residuals. Therefore, in all of these tests, if the P-Value exceeds the predetermined significance level (typically 0.05), we lack sufficient evidence to reject the null hypothesis, indicating that the estimated GARCH model fits the data in terms of the basic assumptions.

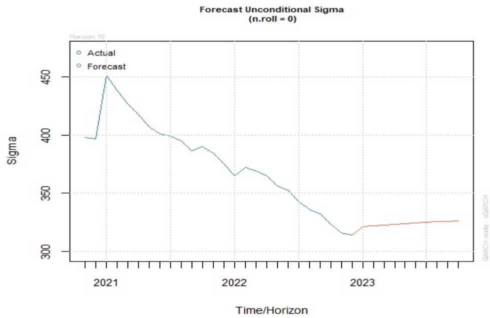
Regarding the testing of parameter stability in the GARCH model, this study employed the Nyblom Stability Test, indicating that the parameters did not significantly change over time. The test results yielded a Joint Statistic value, which is the combined statistical measure assessing the overall stability of the parameters in the GARCH model, of 1.2238. The Joint Statistic value of 1.2238, derived from the Nyblom Stability Test, indicates that the parameters in the GARCH model remain stable over time. This suggests that there is no significant evidence to suggest any substantial shifts or changes in the parameters, implying a consistent behavior in the volatility patterns of the oil and gas export data in Indonesia. The stability of the parameters reinforces the reliability and robustness of the GARCH model in capturing the dynamics of volatility in the dataset.

Subsequently, the Individual Statistics were as follows: mu=0.02142, ar1=0.13010, ma1=0.06078, omega=0.30147, alpha1=0.16904, and beta1=0.18658. The estimated parameter for the mean in the GARCH model is 0.02142. A small value such as this suggests that the mean remains relatively stable over time, indicating that the overall average level of oil and gas exports is not subject to significant fluctuations. The estimated autoregressive parameter signifies the dependence of the current volatility on the previous period's volatility is 0.13010. With a moderate value like this, it implies a moderate influence of the past volatility on the current volatility of oil and gas exports. The estimated moving average parameter suggests the impact of the previous period's forecast error on the current period's error is 0.06078. This relatively small value implies a relatively moderate effect of the previous forecast errors on the current errors in the GARCH model. The parameter omega is 0.30147, in which represents the constant in the GARCH model, signifying the baseline level of volatility. With a value of 0.30147, it indicates a moderate level of baseline volatility in the oil and gas export data. Further, the value of alpha1 is 0.16904. This parameter measures the impact of past volatility on current volatility. With a value of 0.16904, it implies a moderate influence of the past volatility on the current volatility in the GARCH model. On the other hand, the beta parameter reflects the impact of the mean value on the current volatility. A value of 0.18658 suggests a moderate effect of the mean value on the current volatility in the oil and gas export data.

Figure 2 shows the results of the volatility forecast for the next 10 periods. It is useful to understand how volatility is expected to change in the future based on the GARCH (1,1) model used. Figure 2 is an unconditional plot of the time series forecast and the sigma forecast.



(a)



(b)

Figure 2 : (a) Plot Time Series Prediction; (b) Plot Sigma Prediction

Figure 2 (a) is time series prediction (unconditional) showing the unconditional time series forecast plot, which focuses on the general future behavior of the time series based on the model that has been applied. Whereas figure 2 (b) sigma prediction (unconditional) produces an unconditional sigma forecast plot, which is concerned with forecasting volatility or fluctuations in the time series without considering external factors.

From the figure above, it can be seen that the results of the oil and gas forecast analysis for the next 10 periods show a gradual increase from period to period, which shows a consistent upward trend. Using the analysis results in Figure 3, the pattern of volatility fluctuations from period to period can be identified. For example, by looking at the difference between the volatility forecast values for each consecutive period. Suppose the difference between 321.9 and 321.3 is 0.6; the difference between 322.5 and 321.9 is 0.6; the difference between 323.0 and 322.5 is 0.5.

It indicates an increase in volatility over time if the difference tends to increase from period to period. Conversely, if the difference tends to decrease from period to period, it indicates a decrease in volatility over time. From the results of the prediction analysis for the next 10 periods, the relatively consistent differences (e.g., 0.6, 0.6, 0.6) are an indication that volatility fluctuations may be relatively stable from period to period. Meanwhile, a slightly different difference (0.5, 0.5) indicates a possible decrease in volatility fluctuations in certain periods.

In the context of analyzing the prediction of oil and gas in Indonesia, the research findings indicating the differences between the forecasted volatility values for each consecutive period can provide crucial insights into the volatility fluctuations within the industry. Considering that oil and gas are commodities highly susceptible to price changes and global market turmoil, a comprehensive understanding of volatility in production and export can assist stakeholders, including energy corporations, the government, and investors, in making more informed decisions.

IV. CONCLUSION

In conclusion, the forecast indicates that while the mean values of the data remain relatively stable, the volatility levels are expected to increase for several time steps ahead. This can be a critical consideration in the planning and decision-making processes related to oil and gas exports in Indonesia, as heightened volatility can impact the necessary risk assessment and management strategies. Based on the prediction results of the next 10 periods, it can be seen that the differences of the volatility is relatively stable, such as 0.6, 0.6, 06. 6convey the message that volatility changes from one period to another may not be very sharp. Hence, slight variations such as 0.5, 0.5 depict a possible indication of declining volatility variations in some time periods. Thus, based on the forecasted values, the volatility line is considered more or less stable with occasional hints at the reduction in the volatility difference. This stability can play a beneficial part for risk management and/or expectations amongst the stakeholders specifically outlined in the oil and gas export industry. The implications of these findings are particularly significant in the context of national economic policies and corporate decision-making within the international trade sector. The anticipated volatility levels (measured by standard deviation or sigma) continue to increase over time. This indicates that the GARCH model anticipates an escalation in volatility within the oil and gas export data in Indonesia for several time steps ahead.

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