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Vector Autoregressive Model of Crude Oil Product Prices in Nigeria (A Case Study of Crude Oil Product Prices in Nigeria, Data from the National Bureau of Statistics)

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Abstract- This study applies a Vector Autoregressive (VAR) model to forecast oil product prices in Nigeria, specifically petrol (PMS), diesel (AGO), kerosene (NHK), and liquefied petroleum gas (LPG) using data from January 2016 to March 2024. Nigeria's economy is highly sensitive to oil price fluctuations, driven by both domestic and global factors. The VAR model of order 2 effectively captures the interdependencies among the prices of these products and all the equations show very high R-squared values with AGO and NHK performing the best with 99%, followed by LPG and PMS with 98% and 96% respectively. Results reveal significant interrelations and predict an upward trend in oil product prices over the forecast period. The model's predictive accuracy was validated through Root Mean Squared Error (RMSE), 85.83002 for PMS, 213.9482 for AGO, 63.92084 for NHK and 174.9873 for LPG and Mean Absolute Error (MAE) metrics, 76.1557 for PMS, 187.8595 for AGO, 52.4654 for NHK and 151.1315 for LPG. In light of these findings, it is recommended that policymakers adopt strategic measures, such as improving real-time monitoring and building strategic reserves, to stabilize prices and manage economic impacts.

Key words: Oil product Prices, Vector Autoregression, Autocorrelation, Root Mean Squared Error, Volatility.

I. INTRODUCTION

Oil product prices play a critical role in the economy of Nigeria, influencing not only the cost of transportation and goods but also the overall inflation rate and economic stability (Adenikinju, 2009; Akinleye & Ekpo, 2013). As the largest oil producer in Africa and one of the top oil exporters globally, Nigeria's economy is heavily dependent on oil revenues (OPEC, 2023; World Bank, 2022). Despite this wealth of natural resources, the country faces significant challenges in managing oil product prices due to various internal and external factors.

Internally, the dynamics of oil product pricing in Nigeria are affected by government policies, subsidies, and the operational inefficiencies within the domestic refining sector (Akinyetun, 2021; Obioma & Lawal, 2019). The Nigerian government has historically subsidized oil product prices to cushion the populace from the volatility of global oil prices (Fasanya & Onakoya, 2013). However, these subsidies have often led to budgetary strains and have been a source of economic and political debate (Ikpefan & Osuma, 2018). Moreover, the inefficiency and underutilization of Nigeria's refineries have necessitated the importation of refined petroleum products, further complicating the pricing structure (Obi & Okeke, 2014).

Externally, global oil price fluctuations, geopolitical tensions, and international market dynamics significantly impact oil product prices in Nigeria (Hamilton, 2009; Kilian, 2014). The volatility of the global oil market, driven by factors such as supply-demand imbalances, OPEC's production decisions, and geopolitical conflicts, often translates to unpredictable changes in local oil product prices (Ezeaku, 2020; IMF, 2021). This external volatility poses a challenge for economic planning and stability in Nigeria.

Given these complexities, understanding and forecasting oil product prices in Nigeria is crucial for economic planning, policy formulation, and financial management (Adebiyi, Adenuga, & Abeng, 2011). Accurate forecasts can help policymakers design better subsidy schemes, anticipate inflationary pressures, and make informed decisions regarding strategic petroleum reserves and investments in the energy sector (Okonkwo & Worlu, 2019). The Vector Autoregressive (VAR) model offers a robust statistical approach for analyzing multiple time series variables. Unlike traditional single-equation models, the VAR model treats all variables as endogenous, allowing for a more comprehensive analysis of their interdependencies (Sims, 1980; Lütkepohl, 2005). This makes the VAR approach particularly suitable for studying the multifaceted factors influencing oil product prices in Nigeria.

By employing a VAR model, this study aims to provide accurate forecasts of future oil product prices. The findings from this research will contribute to a deeper understanding of the factors driving oil product price changes and offer valuable insights for policymakers and stakeholders in the Nigerian energy sector. The volatility of oil product prices in Nigeria presents significant challenges for the nation's economic stability and development (Olayemi & Akinbobola, 2011). Despite being one of the world's leading oil producers, Nigeria grapples with persistent oil product price fluctuations that disrupt economic planning and adversely affect the cost of living and doing business (Ehinomen & Adeleke, 2012). These fluctuations are influenced by a complex interplay of domestic and international factors, including government policies, subsidies, inefficiencies in the refining sector, and global oil market dynamics (Kpodar & Abdallah, 2017).

The lack of a reliable and accurate forecasting mechanism exacerbates these challenges, leaving policymakers and stakeholders with insufficient tools to anticipate and mitigate the impacts of oil product price volatility (Ezeaku, Asogwa, & Nnaji, 2018). This gap in predictive capability hinders effective economic planning and policy formulation, often resulting in reactive rather than proactive measures.

To address this problem effectively, a sophisticated analytical approach is needed to capture the intricate relationships between oil product prices. The Vector Autoregressive (VAR) model offers a powerful tool for this purpose, as it can model the interdependencies among multiple time series and provide insights for clear understanding and accurate forecasts for future trends and policymaking decisions (Enders, 2015; Gujarati & Porter, 2009). This study seeks to apply the VAR model to forecast future oil product prices in Nigeria. By doing so, it aims to provide a robust analytical framework that can aid policymakers in designing more effective and forward-looking policies to manage oil product price volatility, ensuring greater economic stability and development.

II. LITERATURE REVIEW

Oil product prices are influenced by multiple factors, including global crude oil prices, exchange rates, government policies, and broader macroeconomic conditions. Hamilton (2008) and Kilian (2009) emphasize that fluctuations in global crude oil prices are a major determinant of domestic oil product costs, with geopolitical tensions and supply-demand imbalances contributing significantly to price volatility. In the Nigerian context, additional complexities arise from government subsidies and regulatory interventions. Adenikinju and Odularu (2006) found that while subsidies help stabilize domestic oil product prices, they also create fiscal imbalances and inefficiencies in the energy sector. This underscores the need to strike a balance between affordability and long-term economic sustainability.

Methodologically, time series econometric models have been widely applied to study oil price dynamics. The Vector Autoregressive (VAR) model, introduced by Sims (1980), provides a robust framework for capturing interdependencies among multiple time series variables. Unlike univariate models, VAR treats all variables as endogenous, allowing researchers to analyze their joint evolution over time. The effectiveness of VAR models in economic forecasting has been demonstrated by Stock and Watson (2001) and Lütkepohl (2005). In the context of energy markets, studies such as Zhang et al. (2009) and Apergis and Miller (2009) confirm the suitability of VAR models for capturing oil price dynamics and improving forecast accuracy.

Research applying VAR models to Nigeria remains relatively limited. Olomola and Adejumo (2006), for example, investigated the impact of oil price shocks on the Nigerian economy, showing that shocks significantly affect inflation and output. Similarly, Akinboade et al. (2008) applied a VAR framework to analyze the link between oil prices and economic growth in South Africa, providing a relevant comparative perspective. Their findings demonstrate that oil price shocks exert long-term impacts on economic growth in oil-dependent economies. Abdulkarim et al. (2015) further confirmed that oil price fluctuations strongly influence Nigeria's GDP, inflation, and exchange rates, highlighting the vulnerability of the economy to external shocks.

The role of government policy in shaping Nigeria's oil product prices has been well-documented. Iwayemi and Fowowe (2011) analyzed the effectiveness of policy interventions such as subsidies and price controls, concluding that while such measures mitigate short-term price volatility, they often introduce inefficiencies and fiscal strain. Similarly, Oseni (2013) and Ajayi (2014) evaluated the implications of deregulation, showing its potential to improve efficiency but also raising concerns about affordability and welfare. More recent evidence from Adeniyi and Abiodun (2017) indicates that fuel subsidies continue to exert significant influence on inflation and exchange rates, reflecting the trade-off between policy-driven price stabilization and macroeconomic stability.

Beyond Nigeria, VAR-based analyses of energy markets provide useful insights. Bekiros and Diks (2008) examined interactions between oil prices, interest rates, and stock markets in Europe, while Apergis and Miller (2009) explored the relationship between oil prices and economic growth in African economies, including Nigeria. Their results consistently highlight the sensitivity of oil-dependent economies to global oil price shocks.

From a theoretical standpoint, the dynamics of oil product prices are also explained by Hotelling's (1931) *Theory of Exhaustible Resources*, which links resource scarcity, extraction costs, and long-term market pricing. Complementing this, Box and Jenkins (1970) pioneered the Autoregressive Integrated Moving Average (ARIMA) model, which remains widely applied in analyzing stationary time series. However, multivariate approaches such as VAR have proven more effective for modeling oil product prices in relation to exchange rates, inflation, and global crude oil prices.

Overall, the literature suggests that oil product pricing in Nigeria is shaped by both global market forces and domestic policy interventions. While VAR models have been successfully applied in other contexts, there is still limited application of this framework to Nigeria's oil product price dynamics, presenting an important gap for further empirical investigation.

III. METHODOLOGY

3.1 Study Design and Data Collection

In recent years, the volatility of oil product prices has become a significant concern globally, impacting various sectors of economies and influencing consumer behavior. In Nigeria, where oil product serves as a vital energy source for transportation, industrial activities, and household consumption, understanding the forecasting of oil product prices is of paramount importance for policymakers, businesses, and the general populace. The ability to anticipate changes in oil product prices can enable better decision-making, risk management, and policy formulation, ultimately contributing to economic stability and growth.

The utilized data was derived from secondary source, specifically monthly records of the retail prices of premium motor spirit (PMS) [PETROL], automotive gasoline oil (AGO) [DIESEL], national household kerosene (NHK) [KEROSENE], liquefied petroleum gas (LPG) [GAS] in Nigeria obtained from National Bureau of Statistics (NBS) website (www.nigerianstat.gov.ng). This dataset spans from January 2016 to March 2024, encompassing 8 years and 2 months.

3.2 Statistical Methods

The use of a Vector Autoregressive (VAR) model for analyzing and forecasting oil product prices in Nigeria is grounded in its ability to capture the complex and interdependent relationships among multiple time series variables. However, these models are useful for modelling a single time series data and we have four dependent variables. Therefore, multivariate models were used to model these four variables together. Vector Autoregressive (VAR) is a multivariate time series model and can be used to model more than one variable jointly.

Furthermore, this method is simple and it is not necessary to determine which variable is internal or external (all variables in VAR are endogenous), prediction is simple because the OLS method can be applied to each equation separately and estimates obtained in this method are in many cases better than those obtained from more complex simultaneous equation models

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3.3 Vector Autoregressive Model

Vector autoregression (VAR) is a statistical model used to capture the relationship between multiple quantities as they change over time. VAR is a type of stochastic process model. VAR models generalize the single-variable (univariate) autoregressive model by allowing for multivariate time series. VAR models are often used in economics and the natural sciences.

Christopher Sims (1980) proposed the Vector Autoregression as a multivariate linear time series model in which the endogenous variables in the system are functions of the lagged values of all endogenous variables (each variable is a linear function of past lags of itself and past lags of the other variables). This allows for a simple and flexible alternative to the traditional equations.

The VAR is essentially a generalization of the univariate autoregressive model. Commonly, we notate a VAR as a VAR (p) where p denotes the number of autoregressive lags in the system.

The vector autoregressive model of order 1, denoted as VAR (1), is as follows:

$$Y_{t,1} = c_1 + \Phi_{11}Y_{t-1,1} + \Phi_{12}Y_{t-1,2} + \Phi_{13}Y_{t-1,3} + \Phi_{14}Y_{t-1,4} + \varepsilon_{t,1} \quad (3.1a)$$
$$Y_{t,2} = c_2 + \Phi_{21}Y_{t-1,1} + \Phi_{22}Y_{t-1,2} + \Phi_{23}Y_{t-1,3} + \Phi_{24}Y_{t-1,4} + \varepsilon_{t,2} \quad (3.1b)$$
$$Y_{t,3} = c_3 + \Phi_{31}Y_{t-1,1} + \Phi_{32}Y_{t-1,2} + \Phi_{33}Y_{t-1,3} + \Phi_{34}Y_{t-1,4} + \varepsilon_{t,3} \quad (3.1c)$$
$$Y_{t,4} = c_4 + \Phi_{41}Y_{t-1,1} + \Phi_{42}Y_{t-1,2} + \Phi_{43}Y_{t-1,3} + \Phi_{44}Y_{t-1,4} + \varepsilon_{t,4} \quad (3.1d)$$

Each variable is a linear function of the lag 1 values for all variables in the set.

Where:

- $Y_{t,1}$, $Yt_{,2}$, $Y_{t,3}$ and $Y_{t,4}$ represent the prices of oil products (PMS, AGO, NHK and LPG) at time t.
- $Y_{t-1,1}$, $Y_{t-1,2}$, $Y_{t-1,3}$ and $Y_{t-1,4}$ represent the one-time lagged values of the oil products.
- c_1, c_2, c_3 and c_4 are the intercepts of each equation.
- Φ_{11}, Φ_{12}, Φ_{13} and Φ_{14} are the coefficients that measure the impact of the lagged values of the variables on the current value of each variable.
- $\varepsilon_{t,1}$, $\varepsilon_{t,2}$, $\varepsilon_{t,3}$ and $\varepsilon_{t,4}$ are the error terms or shocks of each equation.

3.4 Stationarity

Stationarity refers to a statistical property of a time series where its mean, variance, and autocovariance are constant over time. Stationarity is a crucial assumption for many time series models, including Vector Autoregression (VAR), because it ensures that the underlying process generating the data does not change over time, making the data more predictable and easier to model.

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine whether a given time series is stationary by testing for the presence of a unit root. A unit root indicates that the time series is non-stationary and possesses a stochastic trend.

The ADF test involves estimating the following regression model:

$$\Delta_{yt} = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t \quad (3.2)$$

Where:

- Δ_{yt} is the first difference of the time series y_t.
- t is a time trend.
- y_{t-1} is the lagged value of the time series.
- Δ_{yt-i} are lagged differences.
- ϵ_t is the error term.

If the test statistic is less than the critical value (i.e., more negative), reject the null hypothesis, indicating the time series is stationary.

3.5 Differencing

Differencing is a technique used in time series analysis to make a non-stationary series stationary. A time series is said to be stationary if its statistical properties, such as mean, variance, and autocorrelation, are constant over time. If these properties change over time, the series is non-stationary. It involves subtracting the previous observation from the current observation to remove trends or seasonality in the data, which can help stabilize the mean of the time series. This process transforms the series into a new series where the differences between consecutive observations are analyzed instead of the actual values.

The first difference of a time series is calculated by subtracting the previous value from the current value.

$$y_t' = y_t - y_{t-1} \quad (3.3)$$

Where y_t is the original value at time t, and y'_t is the first-differenced value at time t.

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Sometimes, one differencing step might not be enough to achieve stationarity. In that case, you can apply differencing again to the already differenced series. This is called the second difference.

3.6 Model Selection

Several criteria are commonly used to determine the optimal lag length in a VAR model. These criteria balance model fit and complexity, penalizing the inclusion of additional parameters. The most widely used criteria include:

3.6.1 Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a widely used statistical measure for model selection, particularly in the context of time series analysis and regression models. It provides a means for comparing different models, balancing model fit and complexity, to select the one that best describes the underlying data.

$$AIC=-2\ln(L)+2k \tag{3.4}$$

where L is the likelihood of the model and k is the number of parameters.

The AIC balances the goodness of fit with the complexity of the model. A lower AIC value indicates a better model.

3.6.2 Final Prediction Error (FPE)

It is a criterion used to select the optimal lag length for the VAR model. It estimates the model's prediction error by considering both the goodness of fit and the complexity of the model.

$$FPE = \left(\frac{T+k}{T-k}\right)^{d} \cdot \frac{det(\Sigma u)}{T} \tag{3.5}$$

Where:

- T is the number of observations.
- k is the total number of parameters estimated in each equation.
- d is the number of equations in the VAR system.
- Σ_u is the estimated covariance matrix of the residuals.

A lower FPE value indicates a better model.

3.7 Model Evaluation for Prediction

Model evaluation for prediction in a Vector Autoregression (VAR) model involves assessing the accuracy and reliability of the forecasts produced by the model. This process ensures that the model can provide useful and actionable insights. Metrics involved in evaluating a VAR model for prediction include:

3.7.1 Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is a measure of the average magnitude of errors in a set of predictions, without considering their direction. It is calculated as the average of the absolute differences between actual values and predicted values. The formula for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3.6}$$

Where:

- n is the number of observations,
- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- $|\cdot|$ denotes the absolute value.

MAE provides a straightforward measure of the average error in the same units as the data.

3.7.2 Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is a measure of the average magnitude of the errors between predicted values and actual values. Unlike Mean Absolute Error (MAE), RMSE gives a higher weight to larger errors by squaring them before averaging and then taking the square root. This makes RMSE more sensitive to outliers. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3.7}$$

Where:

- n is the number of observations,
- y_i is the actual value,
- $\hat{y}_i$ is the predicted value.

RMSE represents the square root of the average of the squared differences between predicted and actual values. It is in the same units as the data, making it easy to interpret in the context of the problem domain.

3.8 Data Analysis and Software

All data related to this project will be subjected to comprehensive data analysis. R statistical Software will be utilized to estimate the model regression using the following libraries: vars for conducting VAR analysis, tseries for handling and analyzing time series data, forecast for time series forecasting and model evaluation, and metrics for assessing the performance of forecasting models.

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IV. RESULTS AND DISCUSSION

4.1 Data Explorative Analysis

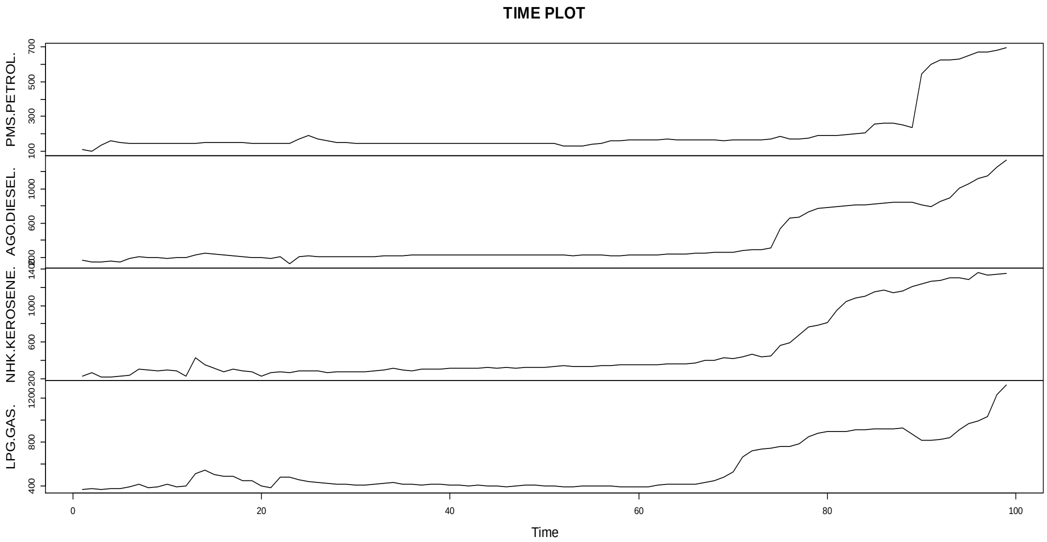

Figure 4.1 Time Plot for Oil Product Prices (January 2016 - March 2024)

Figure 4.1 revealed that all plots follow a steady, flat trend in the early time periods, suggesting stability in oil product prices. The gradual increments in all products start between the 60th and 80th time units, with more noticeable increases in PMS and LPG. This indicates that there were likely common external or internal factors affecting the entire oil market at this point in time, leading to widespread price hikes.

The increments are more pronounced after the 80th time unit, especially in PMS and LPG, where sharp increases suggest significant market shifts. This implies that for the majority of the observed period, oil prices were relatively stable, but external pressures such as changes in policy, market demand, or global price fluctuations led to the significant upward trends observed in the later periods.

4.2 Stationarity Tests

The ADF test was employed to check whether the oil product price series were stationary. The table below shows the results of Augmented Dickey-Fuller Test.

Table 4.1 Augmented Dickey-Fuller Test Results

Variable	Test Statistic	p-value	Stationarity
PMS	-3.9504	0.01462	Yes
AGO	-3.4235	0.0549	Yes
NHK	-3.1639	0.09799	Yes
LPG	-3.2283	0.08731	Yes

Table 4.1 shows that all price series have test statistics less than the critical values at conventional significance levels, with p-values greater than 0.05, indicating that the null hypothesis of a unit root (non-stationarity) can be rejected.

4.3 Vector Autoregressive (VAR) Model Estimation

4.3.1 Model Selection

The appropriate lag length for the VAR model was selected based on the Akaike Information Criterion (AIC) and Final Prediction Error (FPE). The AIC and FPE results are summarized in the table below.

Table 4.2 Lag Length Selection Criteria

Lag Length	AIC	FPE
1	2.816661e+01	1.709115e+12
2	2.815354e+01	1.690121e+12
3	2.827295e+01	1.913310e+12

Table 4.2 shows that the optimal lag length for the VAR model was determined using the Akaike

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Information Criterion (AIC) and Final Prediction Error (FPE). The criteria indicated that a lag length of 2 was most appropriate with the lowest AIC of 2.815354e+01 and FPE of 1.690121e+12, suggesting that a VAR model with 2 lags provides the best balance between fit and complexity.

4.3.2 VAR Model Equation for the Oil Products

The VAR model with two lags was estimated, and the coefficients reveal significant interdependencies among PMS, AGO, NHK, and LPG prices.

M1: PMS Estimated Model:

$$PMS_t = -7.18362 + 0.89863 \cdot PMS_{t-1} - 0.07753 \cdot AGO_{t-1} + 0.12538 \cdot NHK_{t-1} - 0.18412 \cdot LPG_{t-1} + 0.03483 \cdot PMS_{t-2} + 0.01058 \cdot AGO_{t-2} - 0.01346 \cdot NHK_{t-2} + 0.17878 \cdot LPG_{t-2} \quad (4.1)$$

M2: AGO Estimated Model:

$$AGO_t = -98.811670 - 0.005147 \cdot PMS_{t-1} + 0.952297 \cdot AGO_{t-1} + 0.108922 \cdot NHK_{t-1} + 0.004703 \cdot LPG_{t-1} + 0.281542 \cdot PMS_{t-2} - 0.112313 \cdot AGO_{t-2} - 0.198992 \cdot NHK_{t-2} + 0.288928 \cdot LPG_{t-2} \quad (4.2)$$

M3: NHK Estimated Model:

$$NHK_t = -14.13579 + 0.03223 \cdot PMS_{t-1} + 0.12498 \cdot AGO_{t-1} + 0.72037 \cdot NHK_{t-1} - 0.07709 \cdot LPG_{t-1} - 0.09962 \cdot PMS_{t-2} + 0.06437 \cdot AGO_{t-2} + 0.13212 \cdot NHK_{t-2} + 0.16112 \cdot LPG_{t-2} \quad (4.3)$$

M4: LPG Estimated Model:

$$LPG_t = -1.035236 + 0.079371 \cdot PMS_{t-1} - 0.001796 \cdot AGO_{t-1} - 0.114140 \cdot NHK_{t-1} + 1.290373 \cdot LPG_{t-1} + 0.058206 \cdot PMS_{t-2} + 0.138491 \cdot AGO_{t-2} - 0.002282 \cdot NHK_{t-2} - 0.309730 \cdot LPG_{t-2} \quad (4.4)$$

Each equation shows how the current value of a product's price is influenced by its own past values and the past values of other products.

4.3.3 Parameter Estimate and Statistical Significance for Oil Product Prices

The following tables shows the Parameter Estimate of VAR Model of Order 2 for each oil product models.

Table 4.3 Parameter Estimate of VAR Model of Order 2 for M1

Predictors	Estimate	Std. Error	t value	Pr(>|t|)
const	-7.18362	19.59909	-0.367	0.715
PMS_{t-1}	0.89863	0.10757	8.354	8.76e-13 ***
AGO_{t-1}	-0.07753	0.11924	-0.650	0.517
NHK_{t-1}	0.12538	0.10060	1.246	0.216
LPG_{t-1}	-0.18412	0.10874	-1.693	0.094 .
PMS_{t-2}	0.03483	0.11254	0.310	0.758
AGO_{t-2}	0.01058	0.12297	0.086	0.932
NHK_{t-2}	-0.01346	0.10434	-0.129	0.898
LPG_{t-2}	0.17878	0.12321	1.451	0.150

Table 4.3 shows that PMS_{t-1} is highly significant, with an estimate of 0.89863 and a p-value of 8.76e-13, indicating a very strong and reliable predictive relationship. This suggests that the past price of PMS strongly influences its current price. Additionally, LPG_{t-1} shows marginal significance (p-value = 0.094), suggesting a weak negative relationship between past LPG prices and current PMS prices. However, the other variables, such as AGO_{t-1}, NHK_{t-1}, PMS_{t-2}, AGO_{t-2}, NHK_{t-2} and LPG_{t-2}, are not statistically significant, indicating that they are not significant predictors of current PMS prices.

Table 4.4 Parameter Estimate of VAR Model of Order 2 for M2

Predictors	Estimate	Std. Error	t value	Pr(>|t|)
Const	-98.811670	17.539352	-5.634	2.09e-07 ***
PMS_{t-1}	-0.005147	0.096269	-0.053	0.95748
AGO_{t-1}	0.952297	0.106710	8.924	5.88e-14 ***
NHK_{t-1}	0.108922	0.090032	1.210	0.22959
LPG_{t-1}	0.004703	0.097313	0.048	0.96157

PMS_{t-2}	0.281542	0.100717	2.795	0.00636 **
AGO_{t-2}	-0.112313	0.110047	-1.021	0.31024
NHK_{t-2}	-0.198992	0.093378	-2.131	0.03587 *
LPG_{t-2}	0.288928	0.110262	2.620	0.01035 *

Table 4.4 shows that AGO_{t-1} is highly significant (estimate = 0.952297, p-value = 5.88e-14), indicating that the previous period's AGO price is a very strong predictor of its current value. Furthermore, PMS_{t-2} is also significant (p-value = 0.00636), suggesting that the PMS price from two periods ago has a significant positive impact on current AGO prices. NHKt-2 (p-value = 0.03587) and LPG_{t-2} (p-value = 0.01035) also have significant effects, though NHKt-2 has a negative influence. Other variables such as PMS_{t-1}, NHK_{t-1}, LPG_{t-1} and AGO_{t-2} are not significant predictors in this model.

Table 4.5 Parameter Estimate of VAR Model of Order 2 for M3

Predictors	Estimate	Std. Error	t value	Pr(>|t|)
const	-14.13579	21.74410	-0.650	0.517
PMS_{t-1}	0.03223	0.11935	0.270	0.788
AGO_{t-1}	0.12498	0.13229	0.945	0.347
NHK_{t-1}	0.72037	0.11162	6.454	5.75e-09 ***
LPG_{t-1}	-0.07709	0.12064	-0.639	0.524
PMS_{t-2}	-0.09962	0.12486	-0.798	0.427
AGO_{t-2}	0.06437	0.13643	0.472	0.638
NHK_{t-2}	0.13212	0.11576	1.141	0.257
LPG_{t-2}	0.16112	0.13670	1.179	0.242

Table 4.5 shows that the most significant predictor is NHK_{t-1}, which has an estimate of 0.72037 and a p-value of 5.75e-09. This result indicates that the price of NHK from the previous period has a very strong and reliable influence on its current price. However, all other predictors, including PMS_{t-1}, AGO_{t-1}, LPG_{t-1}, PMS_{t-2}, AGO_{t-2}, NHK_{t-2} and LPG_{t-2}, are not statistically significant. This suggests that NHK prices are largely influenced by their own past values, with little to no contribution from the prices of other oil products.

Table 4.6 Parameter Estimate of VAR Model of Order 2 for M4

Predictors	Estimate	Std. Error	t value	Pr(>|t|)
Const	-1.035236	19.452439	-0.053	0.9577
PMS_{t-1}	0.079371	0.106769	0.743	0.4592
AGO_{t-1}	-0.001796	0.118350	-0.015	0.9879
NHK_{t-1}	-0.114140	0.099852	-1.143	0.2561
LPG_{t-1}	1.290373	0.107928	11.956	<2e-16 ***
PMS_{t-2}	0.058206	0.111702	0.521	0.6036
AGO_{t-2}	0.138491	0.122050	1.135	0.2596
NHK_{t-2}	-0.002282	0.103563	-0.022	0.9825
LPG_{t-2}	-0.309730	0.122289	-2.533	0.0131 *

Table 4.6 shows that LPG_{t-1} is highly significant (estimate = 1.290373, p-value < 2e-16), meaning that the price of LPG from the previous period is a very strong predictor of its current price. Additionally, LPG_{t-2} is also significant (p-value = 0.0131), though it has a negative effect, suggesting that earlier prices can also influence current LPG prices, albeit inversely. However, none of the lagged values of PMS, AGO, or NHK, whether from one or two periods ago, show statistical significance in predicting LPG prices, emphasizing the self-reliant nature of LPG prices on their past values.

4.3.4 Model Assessment and Diagnostic Evaluation

Evaluation of the model's performance through key statistical measures like the Residual Standard Error, Multiple R-Squared, Adjusted R-Squared, and p-value. The table below displays the results of the Model Evaluation Metrics.

Table 4.7 Model Evaluation Metrics

Equation	Residual Standard Error	Multiple R-Squared	Adjusted R-Squared	p-value
PMS	30.82	0.9607	0.9571	< 2.2e-16
AGO	27.58	0.9924	0.9918	< 2.2e-16
NHK	34.19	0.9919	0.9912	< 2.2e-16
LPG	30.59	0.9838	0.9823	< 2.2e-16

Table 4.7 provides key metrics for evaluating the model's fit and performance, including Residual Standard Error, Multiple R-Squared, Adjusted R-Squared, and p-values.

The Multiple R-Squared (Coefficient of Multiple Determination) value captures the proportion of variance in the dependent variable that is explained by the independent variables. It measures how well the model fits the data with values closer to 1 indicating a better fit.

Here, all the equations show very high R-squared values, with AGO (0.9924) and NHK (0.9919) performing best. This means that over 99% of the variance in AGO and NHK prices is explained by the model, which suggests excellent predictive power. PMS and LPG also perform well, with R-squared values of 0.9607 and 0.9838 respectively. And this means over 96% and 98% of the variance in AGO and NHK prices is explained by the model respectively.

The Residual Standard Error (RSE) is a measure of the standard deviation of the residuals (prediction errors). Lower RSE values indicate a better fit of the model. In this case, the RSE values for AGO (27.58) and LPG (30.59) are relatively lower compared to the other equations, suggesting these models perform better in terms of accurately predicting the oil product prices.

However, NHK has the highest RSE (34.19), indicating that its predictions are slightly less accurate. Despite the difference in RSE, the values are still reasonable, given the complexity of the data. The p-value tests the null hypothesis that the coefficients of the model are equal to zero (no relationship). A very small p-value (typically < 0.05) indicates that the model's results are statistically significant.

In this case, the p-values for all equations are extremely small (< 2.2e-16), meaning the results are highly statistically significant. This reinforces the reliability of the model for all equations (PMS, AGO, NHK, and LPG).

These metrics suggest that the VAR model is well-specified and capable of capturing the dynamics between the oil product prices.

4.3.5 The Forecast Table

The table below displays the forecasted values for PMS, AGO, NHK, and LPG over the next 12 months.

Table 4.8 Forecasted values for PMS, AGO, NHK, and LPG over the next 12 months.

Period	PMS	AGO	NHK	LPG
24-Apr	681.0570	1467.396	1438.715	1427.729
24-May	664.5055	1615.433	1525.830	1543.355
24-Jun	647.0004	1762.749	1636.101	1663.523
24-Jul	632.0382	1910.491	1765.438	1787.870
24-Aug	621.4084	2057.237	1912.163	1914.020
24-Sep	617.1806	2202.996	2074.257	2039.729
24-Oct	621.0194	2347.848	2249.630	2163.137
24-Nov	634.1926	2491.957	2436.153	2283.042
24-Dec	657.5358	2635.574	2631.706	2398.923
25-Jan	691.4703	2779.116	2834.273	2510.887

25-Feb	736.0368	2923.236	3042.026	2619.588
25-Mar	790.9372	3068.865	3253.417	2726.131

Table 4.8 shows the VAR model generated forecasts for the next 12 months, showing an upward trend in the prices of PMS, AGO, NHK, and LPG. For instance, the forecasted prices of PMS increased from 681.057 NGN in 24-Apr to 790.937 NGN in 25-Mar, indicating a continuous rise in prices.

4.4 Model Evaluation for Prediction

Forecasting accuracy is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which measure the average magnitude of the errors between forecasted and actual values. The results of the MAE and RMSE are presented in the table below.

Table 4.9 Forecasting Accuracy Metrics

Metric	PMS	AGO	NHK	LPG
MAE	76.1557	187.8595	52.4654	151.1315
RMSE	85.83002	213.9482	63.92084	174.9873

Table 4.9 shows that the MAE values are 76.1557 for PMS, 187.8595 for AGO, 52.4654 for NHK, and 151.1315 for LPG. The RMSE values were higher, suggesting the presence of larger deviations in some forecasts, which is expected in volatile markets like oil.

V. SUMMARY AND CONCLUSION

This study utilized a Vector Autoregressive (VAR) model to analyze and forecast oil product prices in Nigeria from January 2016 to March 2024. The analysis included a time plot, stationarity tests, and the estimation of the VAR model with an optimal lag length of 2. The findings highlighted significant variability in oil product prices and the interdependent relationships among these prices over time and evaluating the accuracy of these forecasts using RMSE and MAE metrics.

The study successfully applied a VAR model to forecast the prices of various oil products in Nigeria. The results highlight the model's ability to capture the complex interactions and provide accurate forecasts. The increasing trend in the forecasted prices suggests ongoing upward pressure on oil product prices, this has significant implications for policymakers, businesses, and consumers, highlighting the need for strategic interventions to manage oil price volatility.

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