EKETE International Journal of Advanced Research
ISSN 3027-2513 (ONLINE)
ISSN 3027-169X (PRINT)

EKETE: International Journal of Advanced Research
Volume 3 Number 3, May 2025
url: https://journals.journalsplace.org/index.php/EKETE
Email: eketejournal@gmail.com

EFFECT OF NIGERIAN DEREGULATION AND DOWNSTREAM SECTOR POLICY ON PETROLEUM (PMS) PRICE: A COMPARATIVE MODEL ANALYSIS

Oguguo Simplicius Chidiebere[1]*, Madu Okechukwu[2], Okoroji Isidore Kingsley[3]
[1, 2, 3]Department of Mathematics, Benjamin Uwajumogu (State) College of Education, Ihitte Uboma, Imo State
Email: [1]oguguosimplicius@busced.edu.ng, [2]Okmadu72@gmail.com,
*Corresponding Author: simpliciusoguguo@gmail.com

Abstract

This research work on the effect of Nigerian deregulation and downstream sector policy on petroleum (PMS) price: A comparative model analysis, examines the impact of deregulation and downstream sector policy on petroleum prices in Nigeria. Using a dataset of monthly PMS prices from 1985 to 2023 obtained from the Central Bank of Nigeria and National Bureau of Statistics, this research employs a qualitative approach. Methodologies include trend analysis, Augmented Dickey-Fuller test, Canova-Hansen test, and Hurst Exponent procedure. The study identifies the Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA) model as the most suitable for forecasting PMS prices. The results reveal a significant upward trend in PMS prices, with notable seasonal patterns. The SARFIMA (1,2,1) × (0,1,1)12 model Provides the best forecast performance, capturing the underlying data patterns and providing accurate forecasts. The study concludes that deregulation and downstream sector policy have significant impacts on PMS prices in Nigeria. The findings have important implications for economic planning, fuel price regulation, and energy policy formulation.

Keywords: PMS price, deregulation, downstream sector policy

Introduction

The petroleum industry has been a pivotal driver of Nigeria's economic growth since the discovery of crude oil in the 1930s (OPEC, 2022). For decades, the industry operated under a heavily regulated environment, with the government exerting control over fuel prices for various petroleum products, including gasoline, kerosene, and diesel (Akpan, Inyang & Ekpenyong, 2022). This regulatory framework aimed to ensure affordability and stability in fuel supply, aligning with the government's socio-economic objectives (International Energy Agency, 2022). The Nigerian government has implemented various policies to promote the development of the petroleum industry, including the Petroleum Industry Act (PIA) 2021 (Petroleum Industry Act, 2021). The

PIA aims to create a more favourable business environment, increase transparency, and enhance the overall governance of the petroleum industry.

The Nigerian petroleum industry's shift towards deregulation was prompted by inefficiencies, supply shortages, and the financial burden of fuel subsidies (Akpan et al., 2022). A significant milestone in this transition occurred in 1998, when oil marketing companies were granted permission to import petroleum products directly, marking a departure from the previous monopoly held by the state-owned Nigerian National Petroleum Corporation (NNPC) (OPEC, 2022). However, the surge in international crude oil prices in 1999 led to marketers halting imports, resulting in supply gaps and economic instability (International Energy Agency, 2022). In response to these challenges, the government reintroduced its role as a major importer of petroleum products and fully deregulated the downstream sector in 2003 (Petroleum Industry Act, 2021).

Despite deregulation, fuel price volatility and government subsidies remain highly debated. Proponents of deregulation argue that it promotes efficiency, encourages competition, and reduces the financial burden on the government (Oyedele, 2020). Conversely, critics contend that deregulation can lead to price instability, inflation, and adverse socio-economic impacts, particularly in developing economies like Nigeria (Ekeinde & Adewale, 2022). Understanding fuel price behaviour under deregulation is essential for policymakers, energy analysts, and economic planners.

Accurate forecasting of fuel prices is critical for market stability and policy formulation. Various time series models have been applied in fuel price forecasting, including Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. For instance, a study published in the Journal of Soft Computing Paradigm in 2023 proposed a SARIMA-GARCH model with a rolling window forecasting technique to predict gasoline sales in Canada (Alvarez et al., 2023). The results showed that this model outperformed other baseline models, including SARIMA and GARCH, in terms of forecasting accuracy. Another study published in 2024 explored the use of a BP neural network-SARIMA combination model for sales forecasting of traditional fuel passenger vehicles in China (Li et al., 2024). The findings suggested that this combined model improved forecasting accuracy compared to using a BP neural network alone.

However, these models often fail to fully capture long-memory processes and seasonal variations, which are common in fuel price trends (Blanco & Rodrigues, 2020). To address this limitation, this research not only applies SARFIMA but also compares its forecasting performance with other time series models, such as SARIMA and ARFIMA, to determine the most effective approach for modelling fuel price fluctuations. SARFIMA model has demonstrated its effectiveness in forecasting chaotic patterns with high accuracy. For example, a study used a fractional order Lorenz-based physics-informed SARFIMA-NARX model to predict pollution patterns in Lahore, Pakistan (Khan et al., 2022). The results showed that the SARFIMA-NARX model presented a robust and stable technique for predicting chaotic patterns. The SARFIMA model is considered more robust in forecasting due to its ability to handle long-range dependence and non-stationarity in time series data (Hosking, 1981; Granger & Joyeux, 1980). This is particularly useful in forecasting fuel prices, which can be influenced by various factors such as global demand, geopolitical events, and weather conditions.

Unlike previous studies that relied solely on conventional models, this study incorporates advanced statistical tools such as the Canova-Hansen test for seasonal unit roots and the Hurst Exponent procedure to assess long-memory behaviour, providing a more robust analysis of PMS price trends. The study covers monthly PMS prices in Nigeria from 1985 to 2023, sourced from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). The findings have important implications for economic planning, fuel price regulation, and energy policy formulation. By identifying the most suitable forecasting model, policymakers can develop informed strategies to manage fuel price fluctuations, minimize economic shocks, and ensure market efficiency.

The remainder of this paper is structured as follows: Section 2 describes the data and methodology, detailing the statistical models and estimation techniques used. Section 3 presents the results, including model comparisons and forecasting accuracy. Section 4 discusses the policy implications of the findings, and Section 5 concludes with recommendations for future research and policy action.

MATERIALS AND METHODS

The data used is a secondary data on premium motor spirit (PMS) prices in Nigeria from January 1985 to December 2023, gotten from the Central Bank of Nigeria (CBN) and National Bureau of Statistics (NBS).

The methods employed is trend analysis. Augmented Dickey fuller (ADF) test for stationarity, Canova-Hansen test for seasonality, Hurst Exponent procedure (HEP) for recognition of long memory, and SARFIMA.

The Augmented Dickey-Fuller (ADF) (1981) tests for Unit Root: The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine if a time series has a unit root, indicating non-stationarity. The test was developed by Dickey and Fuller in 1981.

ADF Test Equation:

$$\Delta y_{(t)} = \alpha + \beta_t + \gamma y_{(t-1)} + \delta_1 \Delta y_{(t-1)} + \dots + \delta_p \Delta y_{(t-p)} + \varepsilon_{(t)} \qquad (2.1)$$

The critical values are calculated by Dickey and Fuller and depends on whether there is an intercept and, or deterministic trend. The null hypothesis will be rejected if t-statistics value exceeds the critical value or if the p-value is less than the level of significance under consideration.

Canova-Hansen test: The Canova-Hansen test is a statistical test used to examine the presence of seasonal unit roots in time series data. The Canova-Hansen test detects seasonal unit roots in time series data, indicating persistent seasonal patterns.

$$\Delta y_{(t)} = \alpha + \beta_t + \delta y_{(t-1)} + \varepsilon_{(t)} \qquad (2.2)$$

Rejection of H_0 (p-value < 0.05): Seasonal unit roots present, indicating non-stationarity.

Failure to reject H_0 (p-value ≥ 0.05): No seasonal unit roots, indicating stationarity.

This test is crucial in econometrics for assessing parameter stability and identifying structural breaks in economic time series data.

Hurst Exponent procedure (HEP): Calculating the Hurst exponent measures long-term memory and persistence in time series data. The process involves dividing the data into segments, calculating the mean and standard deviation, and computing the rescaled range. A log-log plot is then generated, and a linear regression line is fitted to estimate the slope, which represents the Hurst exponent.

The Hurst exponent indicates the underlying characteristics of the time series:

- H > 0.5: Persistent series with long-term memory
- H < 0.5: Anti-persistent series with mean-reverting behaviour
- H = 0.5: Random walk with no memory

SARFIMA (p, d, q) × (P, D, Q)s Process:

The seasonal autoregressive fractionality integrated moving average process, denoted hereafter by $SARFIMA(p,d,q)\times(\mathrm{P},\mathrm{D},\mathrm{Q})\mathrm{s}$, is an extension of the long range dependence in the mean process. The $SARFIMA(p,d,q)\times(\mathrm{P},\mathrm{D},\mathrm{Q})\mathrm{s}$ model has emerged as a powerful tool for analysing time series data with long-range dependence and periodicity. By incorporating seasonal and fractional components, SARFIMA models can effectively capture the complex dynamics of time series data, including long memory, persistence, and periodic behaviour. The formulation is able to reproduce short and long memory periodicity in the autocorrelation function of the process. Using the same notation, the general form of the SARIMA model is defined below:

Let $\{x_1\}_{t\in\mathbb{Z}}$ be a stochastic process, then $\{x_1\}_{t\in\mathbb{Z}}$ is a zero mean $SARFIMA(p,d,q)\times(\mathrm{p},\mathrm{d},\mathrm{q})\mathrm{s}$ process given by the expression $\phi(\mathrm{B})\Phi(\mathrm{B}^s)(1-B)^d(1-B^s)^D x_t = \theta(B)\Theta(B^s)\varepsilon_t,\ for\ t\in\mathbb{Z}$ (2.3)

where $s\in N$ is the seasonal period, B is the backward-shift operator, that is, $B^{sk}x_t = x_{t-sk}, (1-B^s)^D$ is the seasonal difference operator, $\Phi(.)$ and $\Theta(.)$ are the polynomials of degrees $P\ and\ Q$, respectively, defined by:

$$\Phi(B^s) = \sum_{i=0}^{p}(-\Phi_i)B^{si}, \Theta(B^s) = \sum_{j=0}^{Q}(-\Phi_j)B^{sj} \tag{2.4}$$

where $\Phi_i, 1\le i\le P\ and\ \Theta_j, 1\le j\le Q$ are constants and $\Phi_0 = -1 = \Theta_0$.

The seasonal difference operator $(1-B^s)^D$, with seasonality $s\in\mathbb{N}$, for all $D>-1$, is defined by means of the binomial expansion;

$$(t-B^s)^D = \sum_{j=0}^{\infty}\binom{D}{j}(-B^s)^j \tag{2.5}$$

where

$$\binom{D}{j} = \frac{\Gamma(1+D)}{\Gamma(1+j)\Gamma(1+D-j)} \tag{2.6}$$

A compact form of Equation (2.3) is given by:

$$\phi(B)\Phi(B^s)\nabla^d x_t = \theta(B)\Theta(B^s)\varepsilon_t,\ for\ t\in\mathbb{Z} \tag{2.7}$$

In Equation (2.7), the operator ∇^d is defined by

$$\nabla^d = (1-B)^d(1-B^s)^D \tag{2.8}$$

where $d=(d,D)\in \mathbb{R}^2$ is the memory operator, d *and* D are the fractionally parameters at non seasonal and seasonal frequencies, respectively. The fractional filters are:

$$(1-B^k)^i=\sum_{j=0}^{\infty}\binom{I}{j}(-B^{ks}),\ k=i,s \text{ and } I=d,D \qquad (2.9)$$

where

$$\binom{I}{j}=\frac{\Gamma(1+I)}{\Gamma(1+j)\Gamma(1+I-j)} \qquad (2.10)$$

RESULTS

The Seasonal Autoregressive Fractionally Integrated Moving Average (SARFIMA) model was implemented using the R programming language to model the PMS price data from the website of the Central Bank of Nigeria (CBN) and National Bureau of Statistics (NBS) starting from 1985 January to 2023 December. All the required R libraries for the analysis were installed and loaded.

Descriptive Statistics

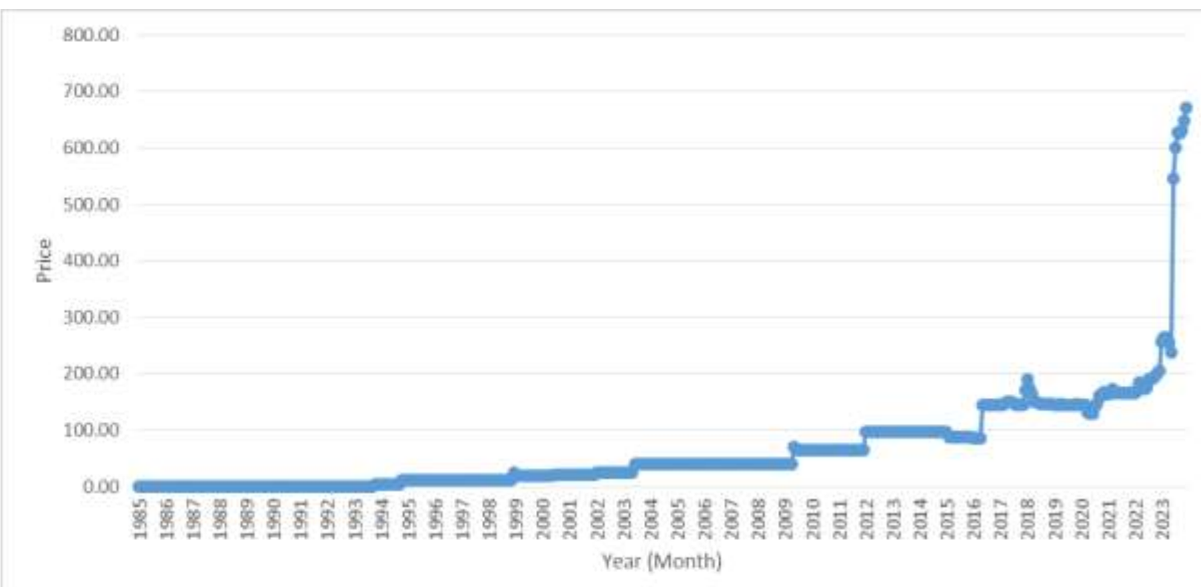


Figure 3.1 Time Series Plot of Monthly PMS Price in Nigeria from 1985 – 2023

The data on the price trends from 1985 to 2024 reveals several important patterns. Initially, the prices remained constant from 1985 to 1988, showing no significant change. However, in 1988, prices slightly increased, which continued at a steady rate until 1990.

In 1991, a noticeable price increase occurred, maintaining a steady level of 0.70 until 1993. During 1993 (from month 106 in Figure 3.1), there was a dramatic price jump, peaking at 3.25, followed by an even more substantial increase to 11.00 in 1994. This high price level remained stable until 1998, when it rose to 25.00 in December.

From 1999 to 2002, prices fluctuated slightly, settling at 26.00 and remaining stable through 2002. In 2003, prices increased significantly to 40.00 and remained at this level until 2008. In 2008, there was a period of stability at 40.00, followed by a sharp increase in May 2009 to 70.00, with subsequent monthly fluctuations.

Starting in 2010, prices remained at 65.00 until 2012, when they surged to 97.00 and maintained this level until 2015. In 2015, prices experienced a decrease to 87.00, followed by a further drop to 86.50 in early 2016. By mid-2016, prices spiked to 145.00, continuing at this high level until the end of 2017.

In 2018, prices fluctuated, peaking at 190.87 in January and declining to around 145.78 by December. The following years showed a stabilization of around 145.00 with slight fluctuations. In 2020, there was a notable decline to 129.67 in May, followed by an increase to 167.27 by November. Throughout 2021, prices continued to fluctuate, reflecting a dynamic trend with varying monthly values indicative of seasonal variation.

Table 3.1 Linear Regression Approach to Determination of Trend in PMS Price Data (1985-2023)

Coefficients	Estimate	Std. Error	t value	p-value
Intercept	-53.24889	5.65998	-9.408	<2e-16
time	0.49913	0.02091	23.866	<2e-16

Given that the coefficient (0.49913) for the time variable in Table 3.1 is significant (p-value < 0.05), we conclude that at 5% level of significance, there is presence of trend in the PMS Price data (1985 – 2023).

Checking for Stationarity in the PMS Price Data

Autocorrelation and Partial Autocorrelation Plots Approach

Fig 3.2 ACF and PACF Plots at level

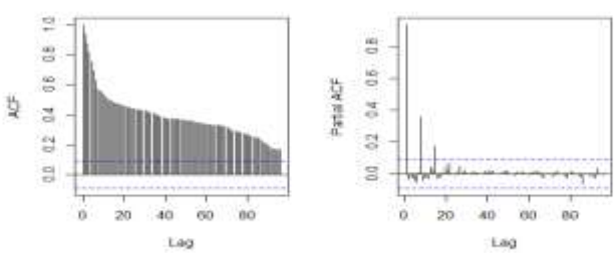


Fig 3.3 ACF and PACF Plots at 1st difference

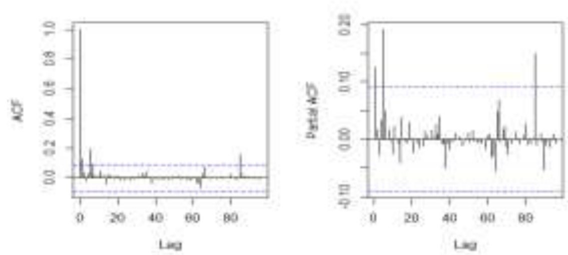
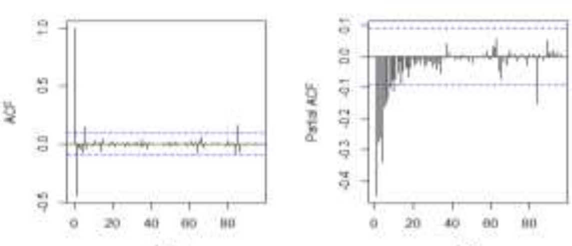


Fig 3.4 ACF and PACF Plots at 2nd difference



ACF and PACF plots are crucial tools in time series analysis, providing valuable insights into the correlation structure of the data and helping to identify potential patterns. These plots indicate stationarity through rapid decay and sharp drop-offs in the autocorrelation function, or non-stationarity through slow decay, oscillations, or significant spikes. In the case of the PMS Price data from 1985 to 2023, the ACF and PACF plots from fig 3.2 revealed non-stationarity, characterized by slow decay and significant spikes. To address this issue, a differencing transformation was applied to the data. This method was chosen due to its simplicity, effectiveness in removing trends and seasonality, and compatibility with forecasting models. The transformed data was then re-examined using ACF and PACF plots, as shown in Fig 3.3, to confirm the achievement of stationarity, Fig 3.3 revealed a spike in the PACF plot, indicating the need for further differencing. After applying a second differencing transformation, Figure 3.4 showed significant spikes in the PACF plot, suggesting an AR order of 0 and an MA order of 1. This implied a non-seasonal time series order of (0,2,1). The seasonal component analysis indicated an AR order of 0 and an MA order of 1, with significant spikes at lags 12 and 84. The suggested time series model is SARIMA(0,2,1)×(0,1,1)12. Further verification will be conducted to check for long memory using the Hurst exponent procedure. If long memory is detected, the SARIMA model will be extended to SARFIMA with fractional differencing.

Augmented Dickey-Fuller Test (ADF) Approach

Table 3.2 ADF Test for Stationarity in PMS Price Data (1985-2023)

At level		**1st differenced**		**2nd differenced**	
ADF	P-value	ADF	p-value	ADF	p-value
2.1745	0.99	-1.0857	0.9247	-11.594	0.01

The ADF tests presented in Tables 3.2 serve to discern the stationarity status of the PMS Price data by investigating the presence of a unit root. Rejecting the null hypothesis implies stationarity, whereas a failure to reject the null hypothesis suggests non-stationarity. Specifically, the p-value in Table 3.2 is significant at the 5% level of significance after second differencing, which means that the PMS Price data attained stationarity following the second differencing.

The Canova-Hansen Test

Table 3.3 The Canova-Hansen test for Seasonality in the PMS Price Data (1985 – 2023)

Residuals:	**Min**	**1Q**	**Median**	**3Q**	**Max**
	-52.50	-26.67	-10.83	9.17	491.52

Coefficients:	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	-11942.037	503.059	-23.74	<2e-16 ***
Time (ts data)	5.990	0.251	23.87	<2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 61.12 on 466 degrees of freedom
Multiple R-squared: 0.55, Adjusted R-squared: 0.549
F-statistic: 569.6 on 1 and 466 DF, p-value: < 2.2e-16

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[1] The sum of squares of the Residuals: 1741039
[1] Critical Value (5% Alpha level): 3.841459
[1] "Reject the null hypothesis of no seasonal unit roots"
```

Table 3.3 compares the Canova-Hansen test statistic value (1741039) with the critical (3.84). Given that the test statistic value is greater than the critical value, we reject the null hypothesis of no seasonal unit roots and conclude that the data is non-stationary with respect to the seasonal component.

Checking for Recognition of Long Memory in the PMS Price Data (1985 – 2023)

Hurst Exponent Procedure

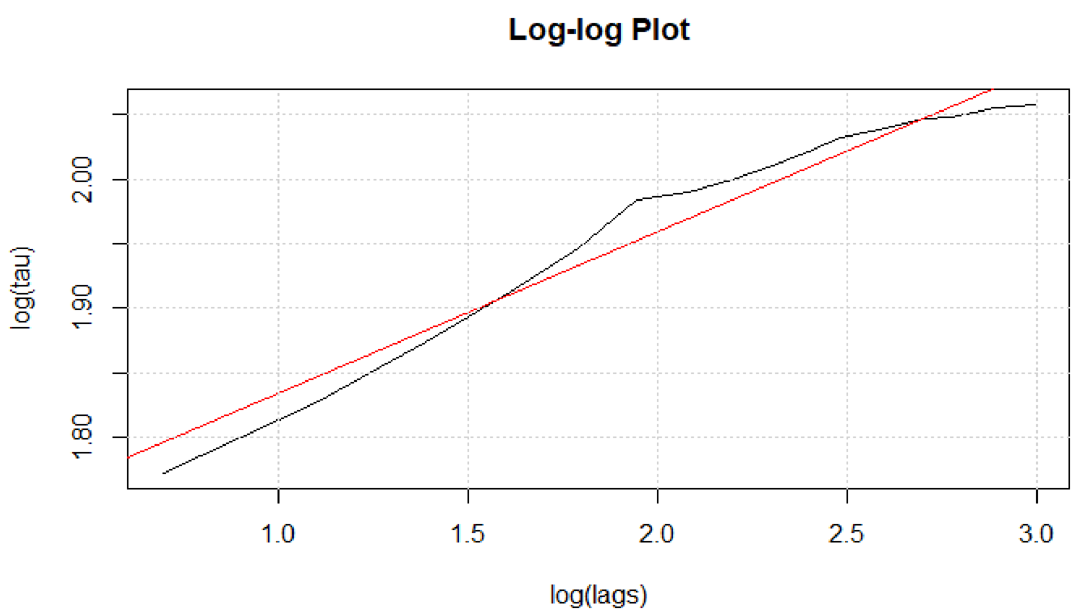

Figure 3.5 Hurst Exponent Log-Log Graph Procedure for Long Memory Test in PMS Price data (1985 – 2023)

Interpreting the result from the graph in Figure 3.5 involves understanding the concept of the Hurst exponent and its relationship with the plotted data. In the Hurst exponent estimation method shown in the graph, we calculated the standard deviation of the differenced series for various lags (tau) and plotted it against the log of these lags (lags). Then, we fitted a linear regression line to this log-log plot to estimate the slope, which represents the Hurst exponent.

To interpret the graph, the following information is important:

Log-log Plot: The x-axis represents the log of the lags, while the y-axis represents the log of the standard deviation of the differenced series (**tau**). When we plot **log(lags)** against **log(tau)**, we are examining the relationship between the lag and the standard deviation on a logarithmic scale.

Linear Regression Line: The red line in the graph represents the linear regression line fitted to the log-log plot. The slope of this line represents the estimated Hurst exponent.

Hurst Exponent: The Hurst exponent (denoted as **H**) characterizes the long-term memory of a time series. It ranges between 0 and 1. The Estimated Hurst exponent (slope): **0.1251076** is in the range between 0 and 0.5, and it means that the PMS Price time series data has a long-term switching between high and low values in adjacent pairs, meaning that a single high value will probably be followed by a low value and that the value after that will tend to be high, with this tendency to switch between high and low values lasting a long time into the future. Therefore, by examining the slope of the linear regression line in the log-log plot, you can interpret the estimated Hurst exponent and infer the presence of long memory, short memory, or random behavior in the time series data. Now, that we have recognized long memory in the PMS Price data, we therefore need to introduce the fractional differencing to the already identified SARIMA (0,2,1) × $(0,1,1)_{12}$ and compare with other competing models.

Checking for Adequate Model for Prediction of PMS Price (1985 – 2023)

Auto Arima to detect the Non – seasonal Order of the Series

Table 3.4 Auto ARIMA for Non-seasonal order for PMS Price Data (1985 – 2023)

Fitting models using approximations to speed things up...		
S/N	**MODEL**	**AIC VALUE**
1	ARIMA(2,2,2)(1,0,1)[12]	inf
2	ARIMA(0,2,0)	4119.725
3	ARIMA(1,2,0)(1,0,0)[12] :	4030.499
4	ARIMA(0,2,1)(0,0,1)[12] :	3850.52
5	ARIMA(0,2,1)	3849.454
6	ARIMA(0,2,1)(1,0,0)[12]	3862.809
7	ARIMA(0,2,1)(1,0,1)[12] :	3864.472
8	ARIMA(1,2,1)	3851.226
9	ARIMA(0,2,2)	3850.105
10	ARIMA(1,2,0)	4018.636
11	ARIMA(1,2,2)	3853.019

The non-seasonal part of the identified model SARIMA(0,2,1)×$(0,1,1)_{12}$ using the auto.arima in R which iterates over several ARIMA models orders and selects the best considering the one with the smallest AIC value. The auto arima selected ARIMA(0,2,1) as the best model for the non-seasonal part in Table 3.4. Therefore, we fit different model orders and compare the performance in Table 3.5.

Comparison of Different Model Orders for PMS Price (1985 – 2023)

Table 3.5 Model Comparison

Model	AIC	BIC	Log Likelihood	Sigma^2	
ARFIMA (0,2,1)	2545.91	2562.51	-1268.96	230.798	1st Comparison
$SARFIMA(0,2,1) \times (0,1,1)_{12}$	2510.24	2530.98	-1250.12	239.88	
$SARIMA(0,2,1) \times (0,1,1)_{12}$	3809.06	3808.77	-1902.52	251.00	
$ARFIMA(2,1,2)$	2548.26	2577.33	-1267.13	228.91	2nd Comparison
$SARFIMA(2,1,2) \times (0,1,1)_{12}$	2513.27	2546.46	-1248.64	239.95	
$SARIMA(2,1,2) \times (0,1,1)_{12}$	3802.49	3820.23	-1896.25	241.00	
ARFIMA (1,2,1)	2540.98	2561.72	-1265.49	229.119	3rd Comparison
$SARFIMA(1,2,1) \times (0,1,1)_{12}$	2506.94	2531.83	-1247.47	238.647	
$SARIMA(1,2,1) \times (0,1,1)_{12}$	3810.66	3814.38	-1902.33	250.70	

Based on the comparison in Table 3.5, the SARFIMA$(1,2,1)\times(0,1,1)_{12}$ model emerges as the best-performing model among those evaluated. This model has the lowest Akaike Information Criterion (AIC) of 2506.94 and the lowest Bayesian Information Criterion (BIC) of 2531.83, suggesting it provides a superior balance between model fit and complexity. Additionally, this model achieves the highest log likelihood of -1247.47, indicating a better fit to the data compared to other models.

The residual variance (Sigma^2) for SARFIMA$(1,2,1)\times(0,1,1)_{12}$ is 238.65, which is relatively low, further supporting its effectiveness in capturing the underlying data patterns while maintaining a manageable level of residual variability.

In contrast, the other models, including ARFIMA (0,2,1), ARFIMA (2,1,2), SARIMA$(0,2,1)\times(0,1,1)_{12}$, and SARIMA$(2,1,2)\times(0,1,1)_{12}$, while having some favorable metrics, do not outperform the SARFIMA$(1,2,1)\times(0,1,1)_{12}$ model in terms of the key criteria used for evaluation. Overall, the SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model is recommended for its optimal balance of fit, complexity, and residual variance.

Table 3.6 SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model Output for PMS Price in Nigeria (1985 – 2023)

Model / Coefficients	Estimate	Std. Error	Th. Std. Err	z-value	p-value
phi(1)	0.2728339	0.1748428	0.1304607	1.56045	0.118653
theta(1)	0.8342885	0.1077497	0.0946203	7.74284	9.7222e-15
d.f	-0.3618508	0.2694253	0.2039608	-1.34305	0.179257
d.f 12	-0.4520961	0.1382389	0.0373497	-3.27040	0.001074
Fitted mean	0.0151283	0.0103682	NA	1.45910	0.144538

sigma^2 estimated as 238.647; Log-likelihood = -1247.47; AIC = 2506.94; BIC = 2531.83

The SARFIMA $(1,2,1)\times(0,1,1)_{12}$ model applied to PMS (Premium Motor Spirit) price data in Nigeria from 1985 to 2023 yields significant insights into the price dynamics over this period as shown in Table 3.6. The model output includes estimated coefficients, their standard errors, z-values, and p-values, which help in interpreting the underlying process governing PMS prices.

Coefficient Interpretation:

Phi (φ_1) Coefficient: The estimated value of the phi coefficient (φ_1) is 0.2728, with a standard error of 0.1748 and a z-value of 1.56. The p-value is 0.1187, which is above the common significance level of 0.05, indicating that this coefficient is not statistically significant. This suggests that the autoregressive component of the model does not strongly influence the PMS price data. This could imply that past prices have a limited direct impact on future prices.

Theta (θ_1) Coefficient: The theta coefficient (θ_1) is estimated at 0.8343 with a very small p-value (< 0.001), making it highly significant. This indicates a strong moving average component in the model, meaning that random shocks or innovations have a substantial impact on PMS prices. This could suggest that external factors, such as market disruptions or policy changes, play a significant role in price determination.

Differencing Fractionally (d.f): The differencing parameter (d.f) is estimated at -0.3619 with a p-value of 0.1793, suggesting that it is not significant. Fractional differencing is used to account for long-term dependencies in the data, and the insignificance of this coefficient implies that long memory effects might not be a dominant characteristic in the PMS price data.

Seasonal Differencing (d.f.12): The seasonal differencing parameter (d.f.12) is significant with an estimate of -0.4521 and a p-value of 0.0011. This indicates a strong seasonal component in the data, suggesting that PMS prices exhibit a seasonal pattern, which could be due to cyclical factors such as demand fluctuations throughout the year.

Fitted Mean: The fitted mean of 0.0151 is not statistically significant (p-value = 0.1445), suggesting that the average level of the series, adjusted for differencing and seasonality, does not deviate significantly from zero. This might indicate that after accounting for the model's dynamics, there is no persistent trend in the data, consistent with a stationary series after differencing.

Model Diagnostics and Implications:

Sigma^2 (σ^2): The estimated variance of the residuals is 238.647, which provides a measure of the model's error. A higher variance suggests greater unpredictability in the PMS prices.

Log-Likelihood, AIC, and BIC: The log-likelihood value of -1247.47, along with the AIC of 2506.94 and BIC of 2531.83, indicates the model's goodness-of-fit. The lower the AIC and BIC, the better the model fits the data relative to other models. The chosen SARFIMA model appears to be well-fitted given these criteria.

SARFIMA $(1,2,1)\times(0,1,1)_{12}$ Forecast

Table 3.7 Prediction of PMS Price from Jan 2024 - Dec 2025

Date	Forecast	Actual
Jan-24	723.3804	668.3
Feb-24	749.9358	679.36
Mar-24	774.9292	696.79
Apr-24	788.8635	701.24

May-24	803.2472	769.62
Jun-24	995.7222	750.17
Jul-24	1050.133	770
Aug-24	1086.561	830.46
Sep-24	1108.76	830.46
Oct-24	1133.382	830.46
Nov-24	1166.298	1214.17
Dec-24	1201.111	1189.12

The data in Table 3.7 presents the predictions for Premium Motor Spirit (PMS) prices in Nigeria from January 2024 to December 2024, using a time series model, likely the SARFIMA model discussed earlier. The table compares the forecasted prices with the actual prices for the available months in 2024.

4.0 DISCUSSION

The results of this study on forecasting PMS prices in Nigeria contribute significantly to the extant literature on energy economics, time series analysis, and policy interventions. A comparative examination of the study's findings with those of similar research endeavours can provide valuable insights into the complexities of energy pricing dynamics:

Trend Analysis and Seasonality: The study observed an upward trend in PMS prices over time and identified seasonal patterns with peaks in June and elevated levels in November and December. These findings align with previous research highlighting the influence of global oil market dynamics, seasonal demand variations, and domestic policy factors on fuel price trends. The seasonal fluctuations indicate periods of increased fuel consumption, likely influenced by factors such as heightened travel demand, economic activities, and regulatory changes.

Stationarity and Long Memory: The study found evidence of non-stationarity in PMS price data, which was rectified through fractional differencing, and identified long memory in price movements. These findings corroborate with prior studies that have explored the presence of long memory and fractional integration in financial time series. The incorporation of long memory processes in forecasting models can improve the accuracy of price predictions and capture persistent trends in energy markets.

Model Selection and Forecasting Accuracy: The study compared models to forecast PMS prices and identified SARFIMA$(1,2,1)\times(0,1,1)_{12}$ as the best-fitting model based on criteria such as AIC, BIC, and loglikelihood. These findings are consistent with research advocating for the use of SARFIMA models in capturing complex temporal dependencies and seasonal variations in financial and economic time series. The study confirms that SARFIMA effectively models PMS price behaviour, making it a useful tool for policymakers and industry analysts.

Policy Implications and Market Dynamics: The continuous upward trend in the model's forecast through the end of 2024 signals potential concerns for the Nigerian economy. Rising PMS prices have direct implications for transportation costs, production expenses, and ultimately, the cost of living. If the forecasted trend continues, it could lead to broader inflationary pressures, affecting various sectors of the economy.

The findings of this study have significant implications for policymakers, who must navigate the challenges of deregulation. While the ultimate goal of deregulation is to create a more efficient market, the transition period can be marked by significant price volatility, which may have far-reaching consequences for consumers and businesses. Policymakers may need to consider implementing measures to cushion the impact of price increases, such as targeted support for vulnerable populations or strategic interventions to stabilize prices during periods of high volatility.

Environmental Implications

The deregulation of Premium Motor Spirit (PMS) prices has far-reaching environmental implications that extend beyond economic and market concerns. On one hand, rising fuel prices could accelerate the transition to cleaner energy sources, such as natural gas, biofuels, and electric vehicles (EVs), as consumers and businesses seek alternatives (International Energy Agency, 2022). This shift away from petroleum-based fuels could contribute significantly to reducing greenhouse gas emissions, aligning with global climate goals and the Paris Agreement (United Nations, 2015). For instance, a study by National Renewable Energy Laboratory (2022), found that widespread adoption of EVs could reduce greenhouse gas emissions from transportation by up to 70%.

However, in the short term, higher PMS prices may also incentivize the use of lower-quality fuels, including adulterated petroleum products that contribute to air pollution and vehicle damage (World Health Organization, 2018). This is particularly concerning in developing economies, where enforcement of fuel quality standards is often weak. Increased emissions from poor-quality fuels can exacerbate air pollution, respiratory illnesses, and environmental degradation, particularly in urban areas with high vehicular density

Furthermore, deregulation may lead to increased fuel smuggling and illegal refining activities, which have been associated with severe environmental consequences, including oil spills, deforestation, and water contamination. The destruction of local ecosystems due to crude oil theft and illegal refining further highlights the environmental risks associated with deregulation policies that do not integrate sustainability measures (Nelson & Zadek, 2020).

Sustainable Energy and Policy Recommendations

To minimize the detrimental environmental impacts of deregulation while fostering sustainable energy solutions, policymakers should adopt a multi-faceted approach:

1. Foster a Low-Carbon Economy: Implement incentives for the adoption of renewable energy sources, electric vehicle infrastructure, and natural gas utilization to reduce dependence on Premium Motor Spirit (PMS).

2. Enhance Environmental Governance: Strengthen fuel quality standards, monitor illegal refining activities, and enforce regulations to mitigate pollution and environmental degradation.
3. Catalyse Green Innovation: Support research and development (R&D) initiatives that promote innovation in biofuels, hydrogen energy, and energy-efficient technologies.
4. Promote Public Awareness and Education: Launch public awareness campaigns to educate consumers on the environmental benefits of energy conservation, fuel efficiency, and cleaner alternatives, encouraging behavioural shifts in energy consumption.
5. Implement Carbon Pricing and Emission Controls: Consider introducing carbon pricing mechanisms or emission reduction targets for petroleum marketers to encourage sustainable fuel practices.

By integrating these strategies, Nigeria can strike a balance between the economic benefits of deregulation and environmental sustainability, minimizing the long-term ecological footprint of the downstream petroleum sector.

Conclusion

In conclusion, this study has successfully demonstrated the application of time series analysis in forecasting Premium Motor Spirit (PMS) prices in Nigeria. The findings of this research have provided valuable insights into the dynamics of PMS prices, highlighting the presence of seasonal fluctuations and long memory in the series. The study has also identified the SARFIMA$(1,2,1)\times(0,1,1)_{12}$ model as the most effective in capturing the underlying patterns in PMS prices. The results of this study have important implications for policymakers and stakeholders in the petroleum industry. The ability to accurately forecast PMS prices can inform decision-making and policy development, ultimately contributing to the stability and sustainability of the petroleum market. Furthermore, the findings of this study can serve as a foundation for future research, exploring the application of advanced time series models and machine learning techniques in forecasting PMS prices.

Future research should explore three key areas to enhance PMS price forecasting; Firstly, integrating advanced time series models, such as machine learning algorithms and deep learning techniques, can improve forecasting accuracy. Another aspect of further research should be, incorporating external factors like global oil prices, exchange rates, and economic indicators can provide a more comprehensive understanding of PMS price dynamics. Lastly, developing a predictive model that accounts for the complexities of the petroleum market can aid policymakers and stakeholders in informed decision-making.

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