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Nonlinear Time Series Models with Regime Switching for Inflation Rate in Nigeria

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Abstract

Inflation is marked by a decline in the domestic currency's value and an increase in its exchange rate relative to foreign currencies. In Nigeria, this depreciation of the Naira has occurred alongside periods of rising inflation. Nonlinear time series models are particularly effective in capturing the complex dynamics of financial data, such as inflation rates. This study models Nigeria's monthly inflation rate using three nonlinear approaches—Logistic Smooth Transition Autoregressive (LSTAR), Self-Excited Threshold Autoregressive (SETAR), and Artificial Neural Networks Time Series (NNETTs)—based on data from the Central Bank of Nigeria (CBN), covering the period from January 2005 to August 2023. Nonlinearity tests by Keenan and Tsay reveal that inflation rates between January 2016 and February 2024 follow a threshold nonlinear process, rejecting the null hypothesis of linearity and confirming the presence of structural breaks in the data. Visual inspection of the series further supports this. Among the models, the LSTAR model demonstrates superior performance with the lowest Akaike Information Criterion (AIC), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE), making it the most effective for modeling the inflation rate. The LSTAR model identifies a critical threshold at 16.46, indicating a regime change in inflation behavior.

Forecasts for September 2023 place the inflation rate at 25.42—well above the threshold—signaling that the economy has entered a higher-inflation regime. This trend continues through January 2024. The study concludes that the LSTAR model is a valuable tool for understanding regime-dependent inflation dynamics and recommends its adoption by analysts and policymakers for more accurate forecasting and strategic economic planning.

Keywords: Inflation; Nonlinear Time Series; LSTAR Model; Threshold Effect; Forecasting; Nigeria

INTRODUCTION

Inflation is the rate of increase in prices of a commodity over a given period of time. Inflation is typically a broad measure, such as the overall increase in prices or the increase in the cost of living in a country. Nyoni and Bonga (2018) defined inflation rate as the persistent and continuous rise in the general prices of commodities. Inflation is characterized by a fall in the value of the country's currency and rise in her exchange rate with other nation's currencies.

Hadrat, Isaac and Eric (2015) stated that high rate of inflation in Nigeria are attributed to factors such as, low output growth rate, high prices of imported products, depreciation in the exchange rate and probably external factors like crude oil price. Since, price stability is one of the main goals objectives of monetary policy; it is up to the policymakers to be forward-looking. Good forecasting ability is suitable to achieve this objective (Hadrat *et al*, 2015). Nigeria is witnessing high inflation with economic and social implications. The high inflation trend in the country has also led to increased demand by workers, especially those in the public sector, for higher wages. Furthermore, the desire to save and invest has been on the decline, adversely affecting economic growth (Hadrat *et al*, 2015).

In statistics, nonlinear regression is a form of regression analysis in which observational data are modeled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variables. Interest in using nonlinear time series methods has recently become popular in the literature. Quite some papers have appeared on the identification, estimation, and testing of nonlinear models.

This rest of this paper organized as follow. Section Two present some review of previous related work, section three contains the research methodology, section four discusses the results and chapter five draws conclusion.

Literature Review

Ahmad (2016) investigated the current account deficit in Mauritius, looking at risks and prospects. He investigated the constant decline, over the last decade, in the exports to gross domestic product (GDP) ratio, which was a cause for concern. Using a three-regime SETAR model and comparing it to the STAR model revealed that the SETAR model performed better than the STAR model and predicted that the Mauritius current account was more likely to switch from surplus to deficit equilibrium than from deficit to surplus.

Yahaya and Matthew (2020) research on "A Markov Regime Switching Approach of Estimating Volatility Using Nigerian Stock Market". Their study examined the volatility on the Nigeria stock market by comparing two Markov regime switching Autoregressive (MS-AR) Models estimated at different lagged values using the Nigeria stock exchange monthly All Share Index data from 1988 to 2018 in the Central Bank of Nigeria (CBN) Statistical Bulletin. It was found that factors like financial crisis, information flow, trading volume, economical aspects and investor's behavior are the causes of volatility in the stock market.

Ani, Egwoh and Hassan (2020) study Application of Self-Exciting Threshold Autoregressive Model on Exchange Rate in Nigeria: A Comparative Approach. In their study, two SETAR models were generated, that is SETAR (2;5,2) model without dummy variable was used as a benchmark, while, dummy variable was added so as to address the identified structural break which generated SETAR (3;5,3). The diagnostic tests revealed that, the SETAR model is adequate for forecasting (i.e. both models are free from serial correlation and heteroscedasticity). The forecast results showed that the SETAR (3;5,3) model with the inclusion of a dummy variable performs better than the SETAR (2;5,2) model without a dummy variable.

Ani and Hassan (2020) researched the Self-Exciting Threshold Autoregressive Model and Endogenous Structural Breaks of Exchange Rate Dynamics in Nigeria: A Bai and Perron Sequential Method. Their study examines structural breaks in Nigeria's exchange rates of the Naira to GBP and USD datasets using average monthly frequency covering from January 2004 to January 2020. The study adopts a Bai and Perron (2003) sequential procedure. The study revealed that both series followed a nonlinear process. The generated SETAR models for NGN/GBP and NGN/USD are SETAR(3;5,3) and SETAR(2;5,4), respectively. The diagnostic test (i.e., Breusch-Godfrey Serial Correlation LM Test and ARCH Heteroscedasticity Test) conducted on both generated models showed that the models are free from serial correlation and heteroscedasticity, which implies that these models are adequate for forecasting NGN/GBP and NGN/USD exchange rates.

Antwi (2017) examined the existence of a nonlinear pattern in monthly inflation for Ghana using nonlinear models. The threshold models, SETAR and LSTAR, were applied to the monthly inflation data obtained from the Ghana statistical service within the period January 1981 to August 2016. Finally, the performance of the threshold models was compared to AR (1) and AR(2) models using minimum values of AIC and BIC. In conclusion, both SETAR and LSTAR models fitted the data best, but in terms of their forecasting ability, the simple AR models outperformed their nonlinear alternatives. Also, it was revealed that Ghana's inflation was likely to experience double-digit inflation in the year 2017.

Aikaterini (2016) investigated the forecast power of Markov regime-switching models for the returns of Canadian, UK, and US daily stock markets. Aikaterini's findings revealed that the regime's transition probabilities were very small, which implies the probability of regime changes is low. Hence, Aikaterini's model is a single regime model since the transition probabilities are very low. The expected duration of regimes staying in the appreciation era is high compared to the depreciation era; however, the impacts were significantly strong in the depreciation era.

Korkpoe and Howard (2019) examined the volatility model for Botswana, Ghana, Kenya, and Nigeria equity markets using the Markov Regime-Switching Bayesian method. They adopted Markov two-regime-switching models to select the best models that describe the markets' returns. They found heterogeneity in the evolution of volatility across the equity markets, and the Markov two regime-switching model described better the heteroscedastic returns generating processes.

Recently, Yahaya and Adeoye (2020) examined Nigeria's stock market volatility by comparing different lags of Markov two Regime-Switching Models. They found that over the years, investors had been exposed to certain risks, and the financial crisis, among others, was the major cause of stock market volatility. However, while the literature on

Markov Regime-Switching has increased recently, there are still limited studies that examine the three regimes, that is, the accumulation or distribution, big-move, and excess or panic regimes, of Nigeria's stock market. It is on this background that this research is being carried out.

Tuaneh, Essi, and Etuk (2021) researched Markov-Switching Vector Autoregressive (MS-VAR) Modelling (Mean Adjusted): Application to Macroeconomic data. A monthly time series of data on total export, total import, exchange rate, and inflation rate spanning from January 2001 to June 2020. The data were obtained from the Central Bank of Nigeria (CBN) Statistical Bulletin 2020. The Markov Switching Vector Autoregressive Model (MSVAR), principally the Markov Switching Mean Vector Autoregressive Model (MSM-VAR), which is a nonlinear modelling method, was used. However, the unit root tests were conducted to ascertain the unit root status of the study variables. The VAR model selected lag length 2, and the MS-MVAR analysis identified two regimes (High and low). The information criteria selected the Markov-Switching Autoregressive Heteroscedastic 2 Vector Auto-regression 2 Model [MSIARH (2)-VAR (2)] as the best model with the least information criteria. The Variance Decomposition of the endogenous variables showed that the variables were self-explanatory in the short run. In the long run, the influence decreased but at a very slow pace. The strong exogeneity of the other variables also increased at a slow pace. The right-hand side variables (supposed exogenous variables) should be tested for endogeneity before the decision on a single equation or system equation estimation.

Therefore, this study intended to compare some nonlinear time series models such as the Additive Autoregressive (AAR) model, Self-Exciting Threshold Autoregressive (SETAR) model, Smooth Transition Autoregressive (STAR) model, and Artificial Neural Networks Modelling (NNETTs) using Nigeria inflation rate datasets.

METHODOLOGY

Method of Data Collection

The time series dataset employed in this study was the Nigeria Inflation Rate. The data was sourced from the Central Bank of Nigeria (CBN) (www.cbn.gov.ng). The data comprises monthly frequency ranging from January 2016 to February 2024. The study used SETAR, LSTAR, and NNETTs models to model the inflation rate in Nigeria. R programming software version 4.1.3 was used for the analysis. The full derivations are available in the original work.

Stationarity test

Augmented Dickey-Fuller (ADF) test

The standard Dickey-Fuller test is considered using the equation

$$\Delta y_t = \alpha y_{t-1} + \varepsilon_t \qquad (3.2.1)$$

Where $\alpha = \rho - 1$ and $\Delta y_t = y_t - y_{t-1}$. The null and alternative hypotheses may be written as:

$$\begin{aligned} &H_o : \alpha = 0 \\ &H_1 : \alpha < 0 \end{aligned} \qquad (3.2.2)$$

and evaluated using the conventional t-ratio for α:

$$t_\alpha = \frac{\hat{\alpha}}{SE(\hat{\alpha})} \qquad (3.2.3)$$

Where $\hat{\alpha}$ is the estimate of α and $SE(\hat{\alpha})$ is the coefficient standard error.

Under the null hypothesis of the unit root test the DF test statistic does not follow the conventional student t-distribution instead asymptotic t-distribution.

Test for Nonlinearity

In order to apply nonlinear time series model to an observable time series, the series must first be nonlinear in nature. That is the existence of nonlinear behavior in the series must first be checked.

Keenan Test

Keenan (1985) to detect non-linearity in an observable time series introduced Keenan test. The test is considered as a special case of the RESET test proposed by Ramsey (1969). It is a special case in the sense that it avoids multicollinearity. As described in Cryer and Chan (2008), the Keenan test for nonlinearity analogous to Tukey's one degree of freedom for non-additivity test. As in Cryer and Chan, the Keenan test is motivated by approximating a nonlinear stationary time series by a second-order Volterra expansion which is given by:

$$y_t = u + \sum_{u=-\infty}^{\infty} \theta_u \varepsilon_{t-u} + \sum_{v=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \theta_{uv} \varepsilon_{t-u} \varepsilon_{t-v} \qquad (3.3.1)$$

Where $\{\varepsilon_t, -\infty < t < \infty\}$ is a sequence of independent and identically distributed with zero-mean random variable. The process $\{y_t\}$ is linear if the double sum of the right-hand side of equation (3.3.1) does not exist.

The Keenan's test statistic for the null hypothesis of linearity ($H_0 : \eta = 0$) is given as:

$$\hat{F} = \frac{\eta^2 (n - 2m - 2)}{RSS - \eta^2} \qquad (3.3.3)$$

Where

m = lag order of the linear autoregressive process

n = sample size considered

RSS = the residual sum of squares from the AR(m) process

When the null hypothesis is satisfied, $\hat{F}$ is approximately F-distributed with 1 and ($n - 2m - 2$) degrees of freedom. The null hypothesis of linearity is rejected if the p-value associated with $\hat{F}$ is small (p-value < α) or when the value of $\hat{F}$ is greater than the selected critical value of the $\hat{F}$ distribution with 1 and $n - 2m - 2$ degrees of freedom.

Tsay's F-Test

Tsay's F-test introduced by Tsay and Tiao (1984) is a test for detecting non-linearity in an observable time series. The test considers a more general nonlinear alternative and is a combined version of the nonlinear test of Keenan (1985), Tsay (1986), and Petruccelli and Davies (1986). For an AR(p) regression with n observation as $y_t = (1, y_{t-1}, ..., y_{t-p})\beta + a_t$ for $t = p+1, ..., n$ where β is a $(p+1)$ dimensional vector of coefficients and a_t is the noise. The author refers to $(y_t, 1, y_{t-1}, ..., y_{t-p})$ as a case of data for the AR(p) model. Then an arranged autoregression is an autoregression with cases rearranged based on the values of a particular regressor. Consider a two regime TAR(2; p,d) model with n observations, the threshold variable y_{t-d} may assume values $\{y_h, ..., y_{n-d}\}$, where $h = \max\{1, p+1-d\}$. Let π_i be the time index of the i^{th} smallest observation of $\{y_h, \ldots, y_{n-d}\}$. Then the arranged autoregression with the first s cases in the first regime and the rest in the second regime is given by:

$$y_{\pi_i+d} = \begin{cases} \phi_0^{(1)} + \sum_{v=1}^{p} \phi_v^{(1)} y_{\pi_i+d+v} + a_{\pi_i+d}^{(1)} & if \;\; i \le s \\ \\ \phi_0^{(2)} + \sum_{v=1}^{p} \phi_v^{(2)} y_{\pi_i+d+v} + a_{\pi_i+d}^{(2)} & if \;\; i > s \end{cases} \tag{3.4.1}$$

where s satisfies $y_{\pi_s} < \tau_i \le y_{\pi_{s+1}}$. The arranged autoregression provides a means by which the observations are separated into groups such that if the true model is indeed TAR(2;p,d) process, the observations in a group follow the same linear autoregressive model. According to the author the separation of the observation does not require knowing the precise value of τ_i and only the number of observations in each group depends on τ_i. But since the threshold value is unknown, however the sequential least square estimates $\hat{\phi}_v^{(1)}$ are consistent for $\phi_v^{(1)}$ if there is sufficiently large number of observations in the first regime.

$$\hat{F}(p,d) = \frac{(\sum \hat{e}_t^2 - \sum \hat{\varepsilon}_t^2)(p+1)}{\sum \hat{\varepsilon}_t^2 / (n-d-b-p-h)} \tag{3.4.9}$$

Where the $\hat{\varepsilon}_t$ is the square residual of equation (16) and the argument (p,d) of $\hat{F}$ is used signify the dependence of the F-ratio on p and d. Suppose that y_t is a linear stationary autoregression process of order p, then for large n the statistic $\hat{F}(p,d)$ follows an asymptotic F distribution with p+1 and $n-d-b-p-h$ degrees of freedom.

The null hypothesis of linearity s rejected if the p-value associated with $\hat{F}(p,d)$ is small (p-value < α) or when the value of $\hat{F}(p,d)$ is greater than the selected critical value of the F-distribution with p+1 and $n-d-b-p-h$ degrees of freedom.

Self-Excited Threshold Autoregressive (SETAR) Model

Self-Excited Threshold Autoregressive (SETAR) Model is a class of the Threshold Autoregressive (TAR) model proposed by Tong (1978) and further discussed in Tong and Lim (1980), Tong (1983, 1990). The SETAR model is a set of different linear AR models, changing according to the value of the Threshold variable(s) which is lagged values of the series. The process is linear in each regime, but the movement from one regime to the other makes the entire process nonlinear. Boero and Marrocu, (2004) gave the two-regime version of the SETAR model of order p as follow:

$$y_t = \begin{cases} \phi_0^{(1)} + \sum_{i=1}^{p^{(1)}} \phi_i^{(1)} y_{t-i} + \varepsilon_t^{(1)} & if \quad y_{t-d} \le \tau \\ \phi_0^{(2)} + \sum_{i=1}^{p^{(2)}} \phi_i^{(2)} y_{t-i} + \varepsilon_t^{(2)} & if \quad y_{t-d} > \tau \end{cases} \tag{3.5.1}$$

Where:

$\phi_i^{(1)}$ and $\phi_i^{(2)}$ are the coefficient in lower and higher regime respectively which needs to e estimated,

τ is the threshold value, $p^{(1)}$ and $p^{(2)}$ are the order of the linear AR model in low and high regime respectively. In this study the order of the AR model in both regimes are equal. y_{t-d} is the threshold variable that governs the transition between the two regimes with d being the delay parameter which is a positive integer ($d < p$); $\{\varepsilon_t^{(1)}\}$ and $\{\varepsilon_t^{(2)}\}$ are sequence of independently and identically distributed random variables with zero mean and constant variance (i.e. *i.i.d.* (0, σ_ε^2)). The two regime SETAR model in its simplest form can be written as SETAR(2,p,d)

LSTAR (Logistic Smooth Transition Autoregressive) Model

The LSTAR model can be viewed as a generalization of the above defined SETAR model:

$$\begin{aligned} X_{t+s} = &\left(\varphi_1 + \varphi_{10} X_t + \varphi_{11} X_{t-d} + \cdots + \varphi_{1L} X_{t-(L-1)d}\right)\left(1 - G\left(Z_t, \gamma, c\right)\right) + \\ &\left(\varphi_2 + \varphi_{20} X_t + \varphi_{21} X_{t-d} + \cdots + \varphi_{2H} X_{t-(H-1)d}\right)\left(G\left(Z_t, \gamma, c\right)\right) + \varepsilon_{t+s} \end{aligned} \tag{3.6.2}$$

with G the logistic function, and Z_t the threshold variable. For Z_t, L and H specification, the same convention as that of SETAR models is followed. In addition, for LSTAR models one has to specify some starting values for all the parameters to be estimated: (ϕ, γ, c). If not provided, f and c starting values are taken from the corresponding SETAR model estimation. Once again, estimation is done using CLS, but here an exact solution does not exist, so a numerical minimization algorithm has to be used. Standard errors provided in the summary are asymptotical, but may not make sense if the error criterion minimization isn't achieved during parameter estimation.

Artificial Neural Networks Modelling (NNETTs)

A neural network model with linear output, D hidden units and activation function g, is represented as:

$$x_{t+s} = \beta_0 + \sum_{j=1}^{D} \beta_j g\left(\gamma_{0j} + \sum_{i=1}^{m} \gamma_{ij} x_{t-(i-1)d}\right) \tag{3.7.1}$$

The only additional argument for specifying this model is the number of hidden unit size, which stands for the above-defined D. For the implementation, the nnet package is used.

RESULTS

Descriptive Analysis

The table below depicts the descriptive statistics of the inflation rate returns covering the period under study. The returns series shows mean value of 16.4476, wth minimum value of 9.62 and maximum value of 31.70, positive skewness and platykurtic (Kurtosis) with flat shape distribution, light tail and less prone to outliers

Table 1: Descriptive Statistic

Statistic	Value
Mean	16.4476
Standard Deviation	4.79103
Variance	22.954
Minimum	9.62
Maximum	31.70
Skewness	1.063
Kurtosis	0.958
Sample	98

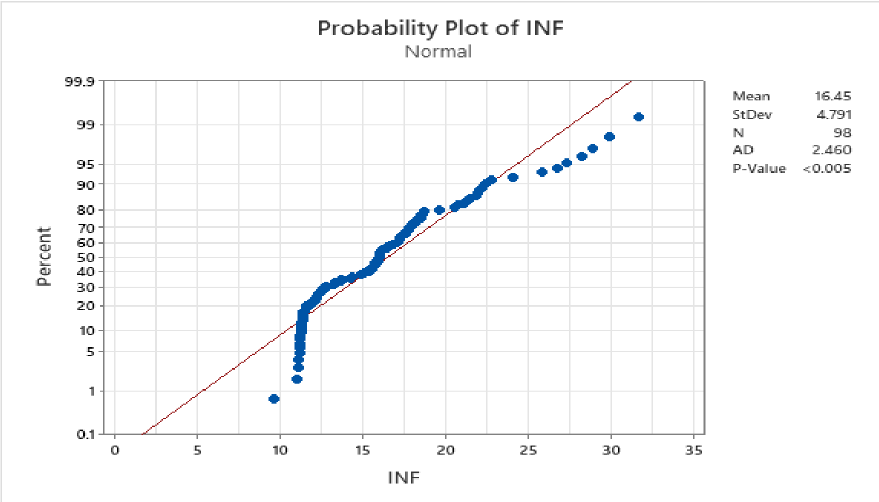

Figure 1: Normal Probability QQ plot of Nigerian Monthly Rate of Inflation

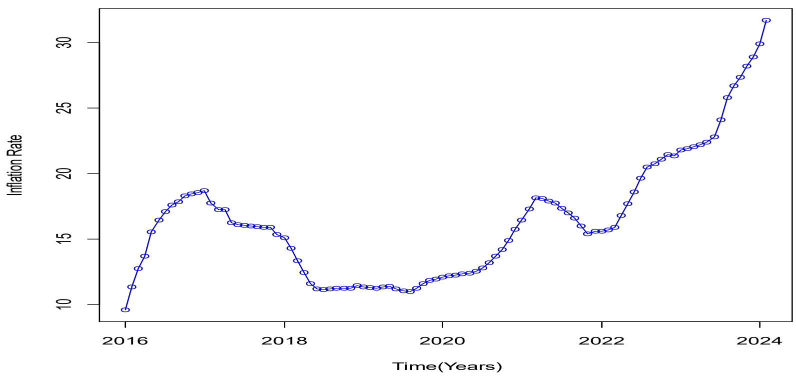

Figure 2: Time series plot of Nigerian monthly rate of inflation (2016-2024)

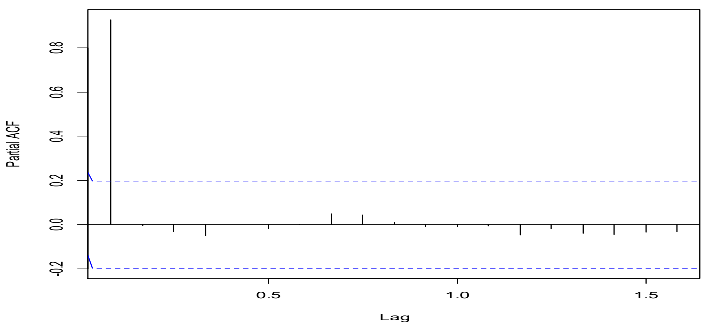

Figure 3: Autocorrelation Function (ACF) Plot for Nigeria Inflation Rate

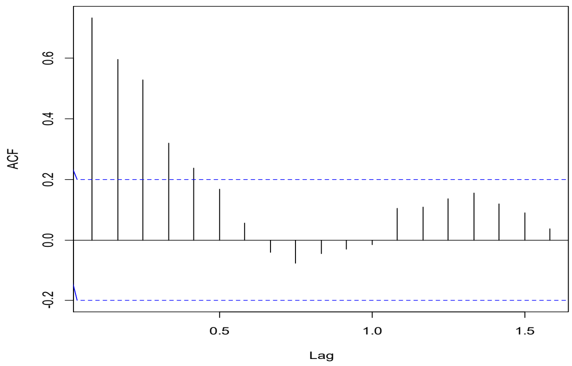

Figure 4: Partial Autocorrelation Function (ACF) Plot for Nigeria Inflation Rate

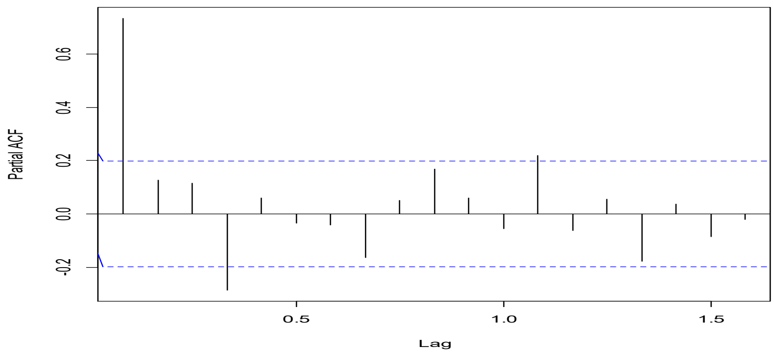

Figure 5: Autocorrelation Function (ACF) Plot for Nigeria Inflation Rate at First Differencing

Unit root test for the monthly rates of inflation in Nigeria (2005-2023)

Table 2: ADF test of Nigeria Monthly Rates of Inflation

Series	Test Statistic	P-Value	Remarks
Inflation Rate	-3.5105	0.04499	Stationary at first differencing

Nonlinearity test for monthly rates of inflation in Nigeria

Table 3: Nonlinearity test for inflation rate

Test	Test Statistic	P-Value
Tsay Test	9.9366	0.00217
Keenan Test	7.3822	0.00784

Model Fitting and Estimation Regime: SETAR Model

Table 4: Grid Search for SETAR Model of order 2 for Monthly Rates of Inflation

	Threshold delay (thDelay)	Low regime (mL)	High regime (mH)	Threshold value	Pooled AIC
1	0	2	2	13.71	43.39314*
2	0	2	2	13.34	44.75824
3	0	2	2	12.77	45.77524
4	0	2	2	13.22	45.90399
5	0	2	2	12.82	46.48335
6	0	2	2	12.40	47.05532
7	0	2	2	12.56	48.16300
8	0	2	2	12.34	48.46134
9	0	2	2	12.48	48.52045
10	0	2	2	12.26	50.89875

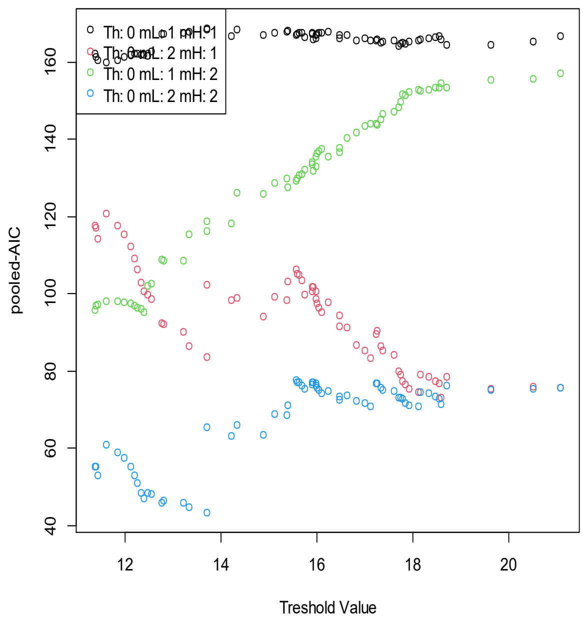

Figure 6: Grid Search for SETAR for Nigerian Monthly Inflation Rate

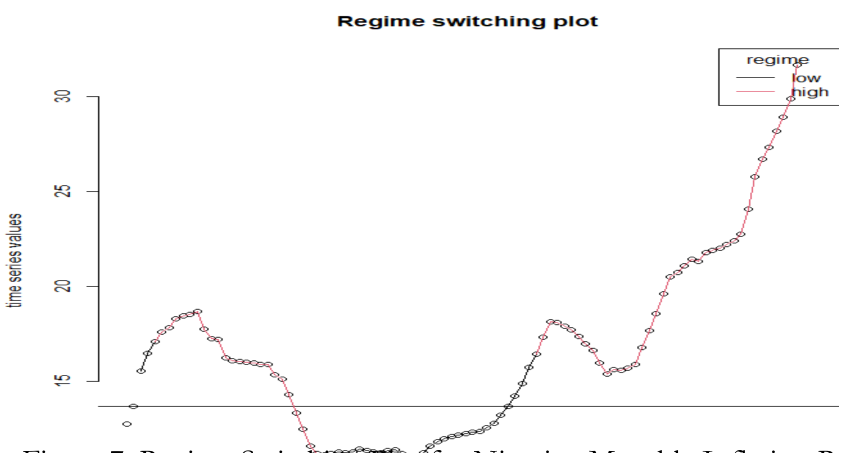

Figure 7: Regime Switching Plot for Nigerian Monthly Inflation Rate

Table 5: Parameter Estimate for Fitting Nigeria Inflation Rate Using SETAR Model

Regimes		Estimate	Standard Error	t-value	P-value
	Constant	0.12746	1.01172	0.1260	0.9000
mL (Low Regime 34.38%)	ϕ_1	1.75017	0.14410	12.1455	0.0000*
	ϕ_2	-0.75758	0.122658	-6.1764	0.0000*
	Constant	-0.34343	0.23599	-1.4553	0.1490
mH (High Regime 65.62%)	ϕ_1	1.76971	0.07753	22.8247	0.0000*
	ϕ_2	-0.74815	0.08164	-9.1638	0.0000*

$$Y_t = \begin{cases} 0.12746+1.75017Y_{t-1}-0.75758Y_{t-2} & Y_{t-2} \geq 13.71 \\ -0.34343+1.76971Y_{t-1}-0.74814Y_{t-2} & Y_{t-2} < 13.71 \end{cases}$$

(4.2)

Table 6: Grid Search for LSTAR Model of order 2 for Monthly Rates of Inflation

	Threshold delay (thDelay)	Low regime (mL)	High regime (mH)	Pooled AIC
1	0	2	2	51.632*
2	0	2	1	52.412
3	0	2	2	52.991
4	0	1	2	53.429
5	1	1	1	53.981
6	1	1	2	54.793
7	1	1	2	55.781
8	1	2	2	56.714
9	2	2	2	57.815
10	2	1	1	58.928

Table 7: Parameter Estimate for Nigeria Inflation Rate Using LSTAR Model

Regimes		Estimate	Standard Error	t-value	P-value
	Constant	0.21589	0.17378	1.2423	0.2141
mL (Low Regime)	ϕ_1	1.73934	0.06352	27.3800	0.0000*
	ϕ_2	-0.75237	0.06414	-11.7286	0.0000*
	Constant	1.48547	1.51172	0.9826	0.3257
mH (High Regime)	ϕ_1	-0.66231	0.32299	-2.0506	0.0403*
	ϕ_2	0.64987	0.31293	2.0767	0.0378*

$$Y_t = \begin{cases} 0.21589+1.73934Y_{t-1}-0.75237Y_{t-2} & Y_{t-2} \geq 22.48 \\ 1.48547-0.66231Y_{t-1}+0.64987Y_{t-2} & Y_{t-2} < 22.48 \end{cases} \quad (4.3)$$

Artificial Neural Networks Modelling (NNETTs) Time Series Model for Nigeria Inflation Rate

A 2-3-1 network with 13 weights

options were - linear output units

Residuals:

Table 8.

Min	1Q	Median	3Q	Max
-7.32245421	-0.74195644	-0.08497754	0.66707167	6.11020113

Table 9: Model Comparison for the Inflation Rates Series

Models	AIC	MAPE	MSE
SETAR	197.6956	0.01411	0.11768
LSTAR	196.2121	0.01373	0.10357
NNETTs	336.7752	0.22599	21.9670

Table 10: Forecast Values for Nigeria Inflation Rate from March, 2024 to December, 2024 Using LSTAR Model

Months	LSTAR
March	32.7784
April	33.7553
May	34.6970
June	35.6111
July	36.4991
August	37.3618
September	38.1999
October	39.0142
November	39.8053
December	40.57384

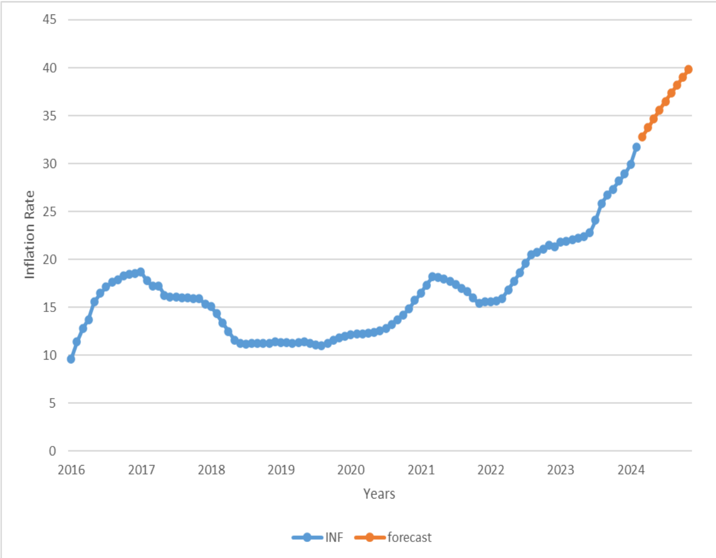

Figure 8: Predict Values for Nigeria Inflation Rate from March to December, 2024 for LSTAR Model

DISCUSSION

This study assesses the appropriateness of both linear and nonlinear models for estimating the monthly inflation rate in Nigeria. The nonlinear model under consideration was LSTAR, SETAR, and NNETTs. The dataset used for this investigation was sourced from the Central Bank of Nigeria's website, covering the period from January 2016 to February, 2024.

Examination of time plots revealed certain trends in the inflation rate data. From 2016 to 2021, there was a noticeable upward and downward trend in inflation rates. Subsequently, from January 2022 to February, 2024, there was a consistent upward trend in inflation rates. The analysis determined that the monthly inflation rate in Nigeria exhibited stationarity at level I(1).

To investigate potential nonlinearity, scatter diagrams were constructed, and Keenan and Tsay tests were conducted on the collected data. These tests indicated that the relationship between the Nigerian monthly inflation rate and its lags was nonlinear. Furthermore, the Keenan and Tsay test, performed on the monthly inflation rates, suggested that the Nigerian inflation rate followed a nonlinear process with a p-value less than 0.05.

Based on the criteria used for model selection, the results showed that the LSTAR model provided a better fit for the Nigerian monthly inflation rate series compared to the SETAR, and NNETTs models. The Logistic Smooth Threshold Autoregressive (LSTAR) model applied to Nigerian monthly inflation data indicates two separate regimes, a "Low Regime" and a "High Regime," each influenced differently by past inflation rates. The low regime is characterized by a non-significant intercept and a significant positive relationship between lagged inflation and current inflation, where a unit increase in the former results in a 1.73934-unit increase in the latter. The transition to the high regime is signaled by a significant negative threshold parameter. Conversely, the high regime features a non-significant intercept and a significant negative relationship between lagged inflation and current inflation, where a unit increase in the former leads to a 0.66231-unit decrease in the latter. The model reverts to the low regime when lagged inflation falls below a significant positive threshold parameter. The forecast indicates an upward trend in the inflation rate from March, 2024 to December, 2024

CONCLUSION

In conclusion, this study reveals that nonlinear patterns in Nigeria's monthly inflation rates covering from January 2016 to March, 2024. Through rigorous nonlinearity tests, specifically the Keenan and Tsay tests confirming the existence of nonlinear dynamics in the dataset. The outcome of this analysis indicated that both SETAR and LSTAR models demonstrated the better fit for the data as compared to other models. Consequently, the LSTAR model emerged as the most appropriate choice for forecasting future monthly inflation rates in Nigeria.

The LSTAR model findings demonstrate that Nigeria's inflation dynamics are regime-dependent, with a clear distinction between low and high inflation periods. In the low inflation regime, past inflation is predictive of an increase in current inflation, while in the high inflation regime, an increase in past inflation typically predicts a decrease in current inflation, suggesting a corrective mechanism that pulls inflation down. The non-significant intercepts in both regimes imply that other factors aside from the constant term may be more influential in determining inflation rates. The statistically significant threshold parameters are key to understanding the nonlinear dynamics of Nigeria's inflation, as they mark the critical levels where the inflationary behavior shifts. The LSTAR model forecasts a consistent month-to-month increase in Nigeria's inflation rate over a 10-month period in 2024. This persistent rise indicates that inflationary pressures are expected to intensify, with no immediate relief in sight for the period under consideration.

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