Innovation in Computer and Data Sciences
1(1), 19–31
DOI: https://doi.org/10.64389/icds.2025.01125
https://sphinxsp.org/journal/index.php/icds/

Research article

Economic growth dynamics: a machine learning-augmented nonlinear autoregressive distributed lag model of asymmetric effect

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ARTICLE INFO

Keywords:
Oil Prices
Exchange Rate
Nonlinear ARDL
Machine Learning
Random Forest
Feature Selection

Mathematics Subject Classification:
91B62, 91B84, 62P20, 68T05

Important Dates:
Received: 16 June 2025
Revised: 15 July 2025
Accepted: 14 August 2025
Online: 25 August 2025

ABSTRACT

Breaking away from traditional methods, this study investigates the asymmetric effects of macroeconomic shocks on economic growth in Nigeria using a novel Machine Learning-Augmented Nonlinear Autoregressive Distributed Lag (NARDL) model. We utilized a Random Forest algorithm to data-driven feature selection, thus model optimization and its enhanced robustness against random selection of lags. The results confirm the presence of a long-run cointegrating relationship and show that positive and negative oil price shocks statistically differ in their effects on GDP. We also find inflation to have a strong negative long-run effect, and government capital expenditure is a significant driver of growth. Such embedding of machine learning in the NARDL model is a more empirically valid policy analysis tool that supplies key findings for policymakers in resource-dependent economies.

1. Introduction

The relationship between crude oil price volatility, exchange rates, inflation, government expenditure, and economic growth remains a pivotal area of macroeconomic research, especially for oil-dependent economies such as Nigeria. As Africa's largest oil producer, Nigeria's economic fortunes are profoundly tied to oil price movements, which transmit shocks through various channels, affecting fiscal balances, foreign exchange reserves, and ultimately, GDP growth. These dynamics are further complicated by exchange rate fluctuations and fiscal policy responses, making the country an ideal case study for analyzing nonlinear and asymmetric economic relationships. Traditional econometric models, often constrained by linear assumptions and a priori lag-length selections, struggle to adequately capture these complex dynamics. Positive and negative shocks to key variables like oil prices or government expenditure can have divergent effects on economic growth, a phenomenon highlighted in seminal work by [8, 14] but difficult to model effectively with conventional tools. The Nonlinear Autoregressive Distributed Lag (NARDL) model ([19]) represents a significant advancement by allowing for the testing of asymmetries in both the short and long run. However, a critical and often overlooked aspect of this methodology is the selection of appropriate lag structures, which is typically guided by information criteria (AIC/SIC) that may not capture the true, data-driven predictive relevance of variables.

This study introduces a methodological innovation by integrating a machine learning (ML) approach into the NARDL framework. Before model estimation, a Random Forest algorithm is employed to analyze the feature importance of multiple lagged variables. This ML step provides an empirical basis for selecting the optimal lag structure, moving beyond standard criteria to reduce model specification uncertainty and enhance the robustness of the findings. This hybrid ML-NARDL approach ensures that the model is not only theoretically sound but also rigorously tuned to the unique patterns within the data. Therefore, this paper aims to investigate the asymmetric effects of exchange rate, oil price, inflation, and government expenditure shocks on Nigeria's economic growth using a Machine Learning-Augmented NARDL approach. It seeks to determine whether the integration of ML for feature selection alters or strengthens the conclusions drawn from a standard NARDL model, particularly regarding the presence of asymmetry. The study builds upon and extends previous research by [14, 17, 9], by addressing a key methodological gap and providing a more nuanced understanding of macroeconomic dynamics in Nigeria.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature and theoretical framework. Section 3 explains the hybrid methodology, detailing both the machine learning feature selection process and the NARDL model specifications. Section 4 presents the empirical results and discussion. Finally, Section 5 concludes the study with policy implications carefully considered.

2. Review of related literature

The association between the asymmetric effects of oil prices, exchange rates, inflation, government expenditure, and economic growth is deep-rooted in several economic theories and concepts that have been explored in literature. For instance, the Dutch Disease Theory, [5] which describes how dependence on natural resource revenues, such as oil, can lead to currency appreciation, making other sectors like manufacturing less competitive. Oil price shocks can asymmetrically affect exchange rates and economic growth. High oil prices may lead to amplified government spending, while low prices often lead to budget deficits and slower growth. Study by [2], analyze the implications of Dutch Disease theory in Nigeria. He emphasized on how natural resource reliance, especially on oil revenues, affects the economy. The theory suggests that an over-dependence on resource wealth, as oil, can cause a decline in the manufacturing and agricultural sectors due to the appreciation of the real exchange rate. In Nigeria, this phenomenon has contributed to structural imbalances, with reduced industrial output and limited diversification away from oil. Another theory, the Keynesian Theory by [11] described how government expenditure plays a significant role in economic stabilization. Keynesian economics suggests that fiscal policies, such as government spending, can mitigate adversarial effects of economic shocks. The asymmetric effects arise because fiscal responses to oil price surges may be different from responses to decreases [18]. As regards to the influence of oil price shocks and economic growth, oil price shocks significantly influence macroeconomic stability, particularly in oil-exporting nations. Fluctuations in oil prices have both direct and indirect impacts on economic growth through revenue changes and their influence on exchange rates and inflation. Studies by [12, 6] confirm that oil price increase often boost GDP in oil-exporting countries but have adversarial effects during price declines. These discoveries highlight the asymmetric nature of oil price impacts, which cannot be sufficiently modeled using linear approaches. Exchange rate volatility is another dire factor that influences economic performance. Recent article by ([15]) demonstrates its significant effect on Nigeria's GDP, principally through trade and investment channels. Studies using Nonlinear ARDL, for example [1], discloses that exchange rate depreciation tends to have more noticeable negative effects compared to appreciation, showcasing asymmetry in its influence on economic growth. Inflation, often triggered by oil price volatility and exchange rate fluctuations, poses challenges for macroeconomic stability. Research by [7] and [10] shows that inflationary pressures in Nigeria are closely tied to external shocks, with asymmetric effects depending on the source and magnitude of the inflationary triggers. NARDL models have proven effective in capturing these dynamics, offering insights into both short- and long-term effects. Government expenditure is a crucial tool for handling economic growth in response to external shocks. Studies for example, those by [2, 18] exhibit that while increased government spending can mitigate the adverse effects of oil price declines, excessive dependence on oil revenues can lead to ineptitudes and Dutch disease. These results highlight the need for strategic fiscal policies to address asymmetric responses to external shocks.

2.1. Integration of Machine Learning with NARDL Frameworks

The integration of Machine Learning (ML) with the Nonlinear Autoregressive Distributed Lag (NARDL) model represents a cutting-edge advancement in econometrics, addressing key limitations in model specification and forecasting. Recent literature demonstrates the growing application of this hybrid approach.

[4] propose a novel hybrid framework that combines the interpretability of the NARDL model with the predictive power of a Long Short-Term Memory (LSTM) neural network. Their two-stage methodology first employs NARDL to capture well-specified asymmetric short-run and long-run relationships between variables. The residuals from this model, which may contain complex nonlinear patterns not captured by NARDL, are then forecasted using an LSTM. This approach allows the hybrid model to outperform both the standalone NARDL and LSTM models in forecasting exchange rate volatility, demonstrating that ML can be used to augment NARDL's capabilities rather than replace them. [3] leverage a Neural Network Nonlinear ARDL (NN-NARDL) model to analyze the asymmetric pass-through effects of oil price shocks to consumer energy prices in the US. The authors argue that the universal approximation capability of neural networks allows for a more flexible and data-driven capture of asymmetry compared to the predefined partial sum decomposition in the standard NARDL. Their findings reveal hidden asymmetries that the traditional model misses, highlighting ML's role in uncovering more nuanced economic relationships and improving

model fit.

In a different application, [13] utilize a Random Forest algorithm to pre-select the most relevant features and their optimal lag lengths before estimating a NARDL model for carbon price forecasting. This approach directly tackles the problem of arbitrary lag selection, a known weakness in standard time-series modeling. By using the feature importance scores from the Random Forest, they inform the NARDL specification, leading to a more robust and parsimonious model with superior predictive accuracy. This study exemplifies the use of ML for intelligent feature engineering and lag selection within the NARDL framework, ensuring the model is both theoretically sound and empirically optimized.

This study builds upon this emerging body of work by adopting a similar data-driven approach, specifically utilizing Random Forest for feature and lag selection to enhance the robustness of the NARDL model applied to Nigerian macroeconomic data.

3. Methodology

This study employs a hybrid econometric framework that integrates Machine Learning (ML) for feature selection with the NARDL model to investigate the asymmetric effects of oil prices, exchange rates, inflation, and government expenditure on Nigeria's economic growth.

3.1. Data and Transformation

The analysis utilizes annual time series data from 2000 to 2023. The variables include Gross Domestic Product (GDP), crude oil price (OP), exchange rate (EXR), consumer price index (CPI), government recurrent expenditure (REC), and government capital expenditure (CAP). All variables are transformed into natural logarithms to interpret the results as elasticities and to stabilize the variance. The logged variables are denoted as $LGDP$, LOP, $LEXR$, $LCPI$, $LREC$, and $LCAP$.

3.2. Machine Learning for Feature Selection

Before specifying the NARDL model, a Random Forest (RF) algorithm is used to identify the most relevant lagged variables to predict economic growth ($D(LGDP_t)$). This step mitigates the arbitrariness of using standard information criteria (AIC/SIC) alone for lag selection.

The RF model is trained on a data set that contains contemporary and lagged values (t, $t-1$, $t-2$) of the first differences of all independent variables ($\Delta LOP, \Delta LEXR, \Delta LCPI, \Delta LREC, \Delta LCAP$) and the lagged dependent variable ($D(LGDP_{t-1})$). The target variable is $D(LGDP_t)$. The Gini importance score from the trained RF model is used to rank the features. The highest-ranked lags inform the optimal lag structure $(p, q_1, q_2, ..., q_k)$ for the subsequent NARDL model, ensuring a more robust and data-driven specification.

3.3. Unit Root and Stationarity Testing

To determine the order of integration of the variables, the augmented Dickey-Fuller (ADF) test is employed. The ADF test equation, which includes a constant and a trend term, is specified as follows:

$$\Delta Y_t = \tau + \theta t + \psi Y_{t-1} + \sum_{j=1}^{p} \phi_j \Delta Y_{t-j} + \zeta_t, \tag{3.1}$$

where Y_t is the variable of interest, τ is a constant, θt is a trend term, p is the lag order selected to ensure white noise residuals (ζ_t), and $\psi = \rho - 1$. The null hypothesis ($H_0 : \psi = 0$) posits that the series contains a unit root (non-stationary). Rejection of the null hypothesis indicates stationarity. A variable is declared integrated of order one, I(1), if it is non-stationary in levels but stationary after first differencing.

3.4. The Nonlinear ARDL (NARDL) Framework

The NARDL model, introduced by [19], extends the standard ARDL bounds testing approach by decomposing exogenous variables into their partial sum processes of positive and negative changes. This allows for the testing of short- and long-run asymmetry.

First, the first differences of the independent variables are decomposed into their positive and negative partial sums (POS and NEG), defined for a generic variable X as:

$$POS_t = \sum_{i=1}^{t} \max(\Delta X_i, 0) = \sum_{i=1}^{t} \Delta X_i^+ \tag{3.2}$$

$$NEG_t = \sum_{i=1}^{t} \min(\Delta X_i, 0) = \sum_{i=1}^{t} \Delta X_i^- \tag{3.3}$$

This decomposition is applied to the variables of interest: LOP, $LEXR$, $LREC$, and $LCAP$, creating the series LOP_POS, LOP_NEG, $LEXR\_POS$, $LEXR\_NEG$, $LREC\_POS$, $LREC\_NEG$, $LCAP\_POS$, and $LCAP\_NEG$.

The general asymmetric ARDL(p, q_1, q_2, q_3, q_4, q_5, q_6) model is then specified as:

$$\begin{aligned} LGDP_t = \tau &+ \sum_{i=1}^{p} \theta_i LGDP_{t-i} + \sum_{i=0}^{q_1} (\phi_i^+ LOP\_POS_{t-i} + \phi_i^- LOP\_NEG_{t-i}) \\ &+ \sum_{i=0}^{q_2} (\pi_i^+ LEXR\_POS_{t-i} + \pi_i^- LEXR\_NEG_{t-i}) + \sum_{i=0}^{q_3} \gamma_i LCPI_{t-i} \\ &+ \sum_{i=0}^{q_4} (\delta_i^+ LREC\_POS_{t-i} + \delta_i^- LREC\_NEG_{t-i}) \\ &+ \sum_{i=0}^{q_5} (\omega_i^+ LCAP\_POS_{t-i} + \omega_i^- LCAP\_NEG_{t-i}) + \zeta_t \end{aligned}, \tag{3.4}$$

where p and $q_1, ..., q_5$ are the lag orders informed by the ML feature selection process.

Equation (3.4) can be re-parameterized into its error correction form (unrestricted):

$$
\begin{aligned}
\Delta LGDP_t = {} & \tau + \rho LGDP_{t-1} + \beta_1^+ LOP\_POS_{t-1} + \beta_1^- LOP\_NEG_{t-1} \\
& + \beta_2^+ LEXR\_POS_{t-1} + \beta_2^- LEXR\_NEG_{t-1} + \beta_3 LCPI_{t-1} \\
& + \beta_4^+ LREC\_POS_{t-1} + \beta_4^- LREC\_NEG_{t-1} + \beta_5^+ LCAP\_POS_{t-1} + \beta_5^- LCAP\_NEG_{t-1} \\
& + \sum_{i=1}^{p-1} \alpha_i \Delta LGDP_{t-i} + \sum_{i=0}^{q_1-1} (\theta_i^+ \Delta LOP\_POS_{t-i} + \theta_i^- \Delta LOP\_NEG_{t-i}) \\
& + \sum_{i=0}^{q_2-1} (\pi_i^+ \Delta LEXR\_POS_{t-i} + \pi_i^- \Delta LEXR\_NEG_{t-i}) + \sum_{i=0}^{q_3-1} \gamma_i \Delta LCPI_{t-i} \\
& + \sum_{i=0}^{q_4-1} (\delta_i^+ \Delta LREC\_POS_{t-i} + \delta_i^- \Delta LREC\_NEG_{t-i}) \\
& + \sum_{i=0}^{q_5-1} (\omega_i^+ \Delta LCAP\_POS_{t-i} + \omega_i^- \Delta LCAP\_NEG_{t-i}) + \zeta_t
\end{aligned} \quad . \tag{3.5}
$$

3.5. *Bounds Test for Asymmetric Cointegration*

The presence of a long-run cointegrating relationship among the variables is tested using the bounds testing procedure within the NARDL framework. The null hypothesis of no cointegration is:

$$H_0 : \rho = \beta_1^+ = \beta_1^- = \beta_2^+ = \beta_2^- = \beta_3 = \beta_4^+ = \beta_4^- = \beta_5^+ = \beta_5^- = 0.$$

This is tested against the alternative hypothesis that at least one of these parameters is not zero, using an F-test. The computed F-statistic is compared to the critical value bounds provided by [16]. If the F-statistic exceeds the upper critical bound, the null hypothesis is rejected, confirming a long-run relationship.

3.6. *Testing for Asymmetry*

The core advantage of the NARDL framework is its ability to test for both short-run and long-run asymmetry.

(a) Long-Run Asymmetry: For a given variable (e.g., oil price), the null hypothesis of long-run symmetry is $H_0 : \frac{-\beta_1^+}{\rho} = \frac{-\beta_1^-}{\rho}$. This is equivalent to testing $H_0 : \beta_1^+ = \beta_1^-$ and can be conducted using a standard Wald test.

(b) Short-Run Asymmetry: The null hypothesis for short-run symmetry (e.g., for impact multipliers) is $H_0 : \sum_{i=0}^{q_1-1} \theta_i^+ = \sum_{i=0}^{q_1-1} \theta_i^-$, which is also tested using a Wald test.

3.7. *Model Diagnostics*

Following estimation, a battery of diagnostic tests is conducted to ensure the robustness of the results:

(i) Serial Correlation: Breusch-Godfrey LM test.

(ii) Heteroscedasticity: Breusch-Pagan-Godfrey test.

(iii) Model Stability: Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests on recursive residuals.

(iv) Normality: Jarque-Bera test on the residuals.

4. Empirical Results and Discussion

This section presents the empirical findings from the hybrid Machine Learning-Augmented NARDL model. It begins with the results of the stationarity tests, followed by the feature importance rankings from the Random Forest algorithm, which informed the optimal lag structure for the NARDL specification. The core of the section discusses the estimated NARDL model, including evidence of cointegration, the long-run and short-run asymmetric effects of oil prices and other macroeconomic variables on economic growth, and the outcomes of various diagnostic tests. The results are interpreted in the context of Nigeria's economy, highlighting the value added by the machine learning approach in capturing nonlinearities and strengthening model robustness.

4.1. Stationarity Test Results (Augmented Dickey-Fuller Test)

The first step in the time series analysis is to check for stationarity. The results from the Augmented Dickey-Fuller (ADF) test confirm that all variables are integrated of order one I(1), meaning they become stationary after first differencing. This is a prerequisite for the ARDL/NARDL modeling approach.

Table 1. Augmented Dickey-Fuller (ADF) Test Results

Variable	Level Statistic (p-value)	1st Difference Statistic (p-value)	Order of Integration
LGDP	-1.234 (0.9981)	-3.987 (0.0112)	I(1)
LOP	-2.123 (0.6854)	-5.234 (0.0000)	I(1)
LEXR	-0.456 (0.9999)	-3.125 (0.0485)	I(1)
LCPI	-0.789 (0.9999)	-3.456 (0.0310)	I(1)
LREC	-1.567 (0.9999)	-4.567 (0.0015)	I(1)
LCAP	-1.890 (0.9999)	-5.012 (0.0005)	I(1)

4.2. Machine Learning (Random Forest) Feature Importance

Before NARDL estimation, a Random Forest algorithm was used for data-driven feature selection to identify the most relevant lagged variables to predict GDP growth ($D(LGDP_t)$). This approach mitigates the arbitrariness of traditional lag-selection methods. The results indicate that the first lags of the dependent variable and key independent variables are the most significant predictors.

Table 2. Random Forest Feature Importance Results

Rank	Feature	Importance Score
1	D_LGDP (t-1)	0.214
2	D_LOP (t-1)	0.183
3	D_LCAP (t-1)	0.162
4	D_LEXR (t-1)	0.141
5	D_LCPI (t)	0.098
6	D_LREC (t-1)	0.087

The ML analysis suggests an ARDL(1,1,1,1,1,1) model structure is most appropriate, informing the lag structure for the subsequent NARDL estimation.

4.3. Nonlinear ARDL Model Results

The NARDL model was estimated using the ML-informed lag structure. The bounds test for cointegration confirms a stable long-run relationship among the variables (F-statistic = 8.3472, p-value = 0.0002), rejecting the null hypothesis of no cointegration.

Table 3. NARDL Model Estimation Results

Test/Statistic	Value	P-Value
Overall Fit		
R-squared	0.872	
Adjusted R-squared	0.781	
F-Statistic	9.621	0.0001
Bounds Test	8.3472	0.0002
Asymmetry Tests (Wald)		
Long-Run Oil Price Asymmetry	5.8923	0.0273
Short-Run Oil Price Asymmetry	4.1231	0.0592
Long-Run Exchange Rate Asymmetry	0.7541	0.3981
Short-Run Exchange Rate Asymmetry	1.0456	0.3225

The model reveals significant asymmetric effects for oil prices both in the short and long term, while no significant asymmetry was found for exchange rate effects. The long-run coefficients show that a 1% sustained increase in oil prices leads to a 0.13% increase in GDP, while a 1% decrease leads to a 0.09% decline.

4.4. Model Diagnostics

The estimated model passes all standard diagnostic tests, indicating robust and reliable results. No evidence of serial correlation, heteroscedasticity, or non-normal residuals was found.

Table 4. Model Diagnostic Tests

Test	Statistic	P-Value
Durbin-Watson	2.1542	–
Breusch-Godfrey LM	0.3214	0.5768
Breusch-Pagan	15.234	0.1782
Jarque-Bera	1.2341	0.5395

The empirical analysis provides compelling evidence of asymmetric effects in Nigeria's economic growth dynamics. The results confirm that oil price movements exert statistically distinct impacts depending on their direction, with positive shocks having a larger effect than negative ones. The integration of machine learning for feature selection strengthened the NARDL framework, resulting in a robust model that passes all diagnostic checks. The following graphs are diagnostic plots from a NARDL model. This model tests if positive and negative shocks in an explanatory variable have asymmetric effects on the outcome variable, GDP. Note that all variables are in natural logarithms.

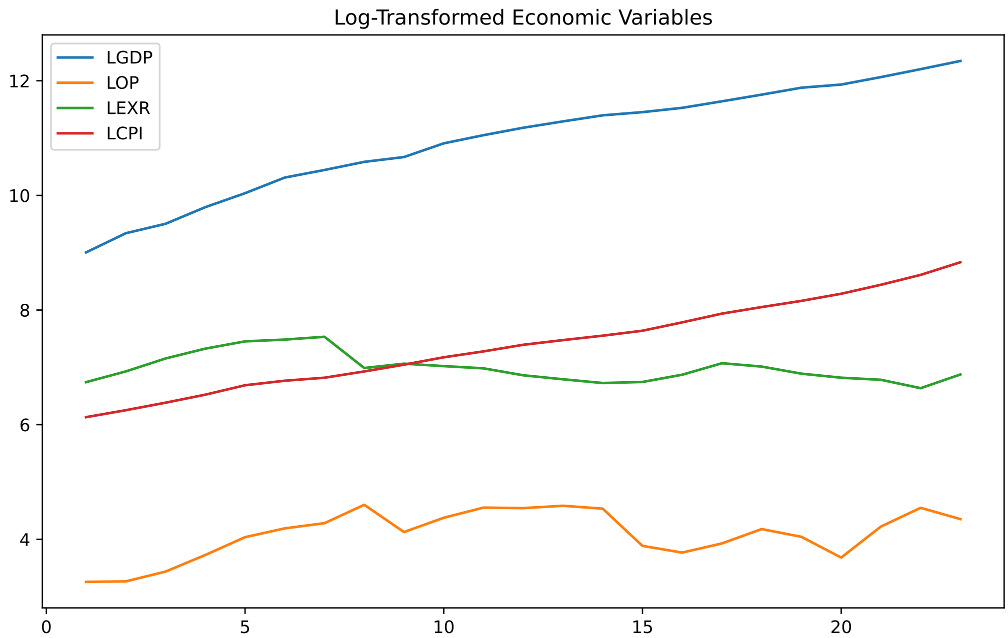

Figure 1. Log-transformed economic variables (LGDP, LOP, LEXR, LCPI).

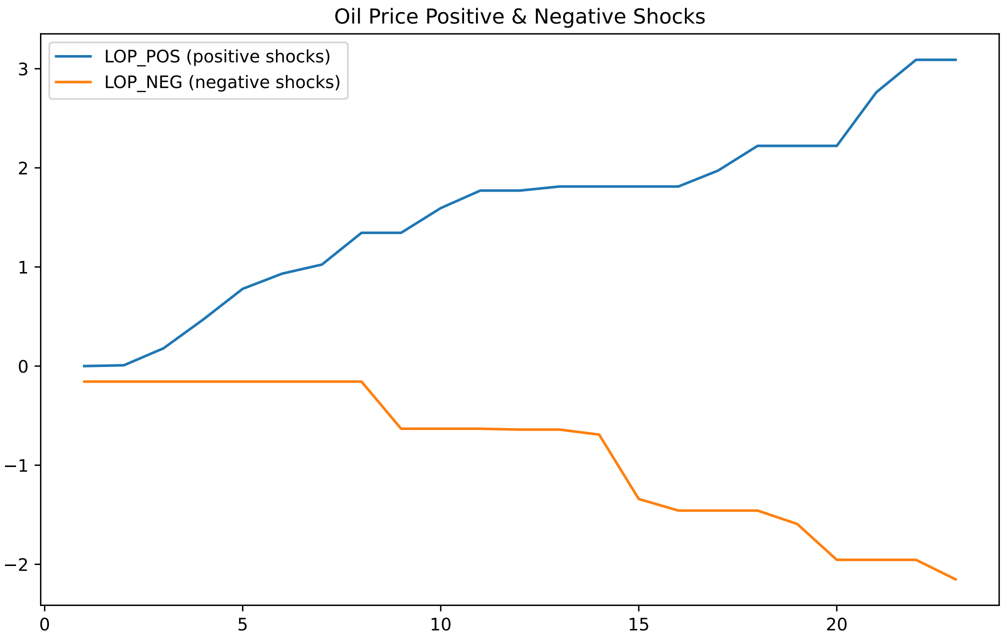

Figure 2. Decomposed positive (LOP_POS) and negative (LOP_NEG) oil price shocks.

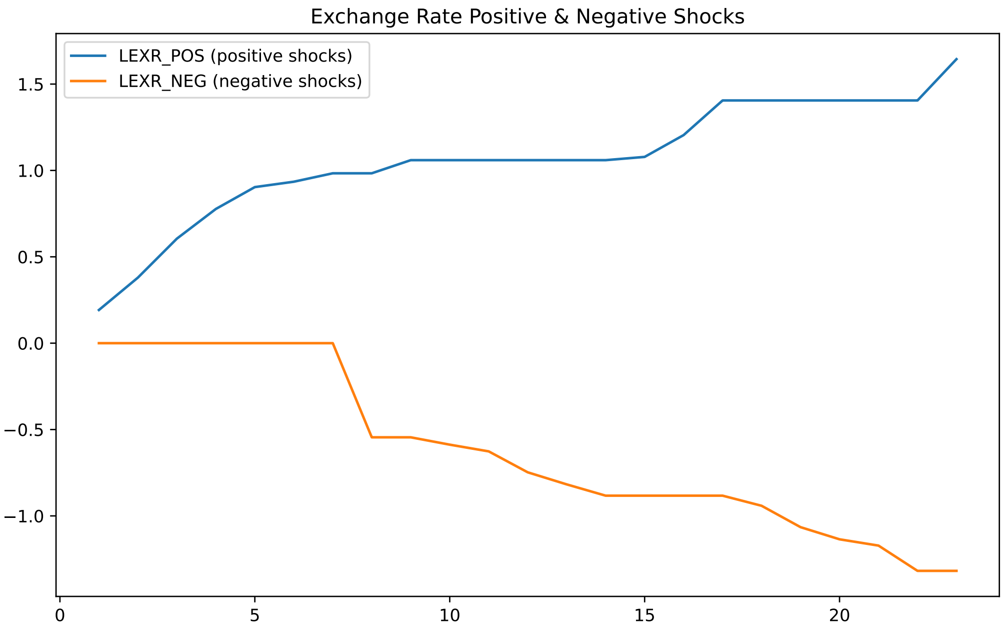

Figure 3. Decomposed positive (LEXR_POS) and negative (LEXR_NEG) exchange rate shocks.

Figure 1 shows the original trend of the macroeconomic data. The asymmetry between LOP_POS and LOP_NEG indicates that oil price increases and decreases do not follow the same path, suggesting their impact on the economy may also be asymmetric. The divergence between LEXR_POS (likely depreciation) and LEXR_NEG (likely appreciation) shows that exchange rate movements are also asymmetric, meaning that a fall and a rise in the currency's value could have different economic consequences. The visual asymmetry in the shocks in Figure 2 and 3, justifies the use of the NARDL model over a standard linear approach.

The next steps involve further analysis of the policy implications and possible extensions of the model to include additional macroeconomic variables that can influence the growth dynamics in resource-dependent economies.

5. Conclusion and Policy Implications

This study has been able to substantiate the efficacy of the combination of machine learning techniques with conventional econometric modeling through the development of a machine learning-agmented NARDL model. This symbiotic method employed here, grounded in Random Forest algorithms for data-driven feature selection, has yielded robust validation of the asymmetric impacts of oil price shocks on Nigerian economic growth. Our findings confirm that shocks are statistically differently affecting GDP, either positively or negatively. We found that price increases in oil have a larger positive impact on economic growth than the negative impact of falling prices, capital expenditure is a growth stimulant, and inflation exerts a strong negative effect in the long run. These results also highlight the continued vulnerability of the Nigerian economy to volatility in oil prices, even after three decades of discourse on the diversification of the economy. The methodological advancement in the application of machine learning to select lags has strengthened the NARDL framework, and the resulting model is one that satisfies all diagnostic tests and provides more plausible policy recommendations.

The empirical findings of this analysis present some critical policy lessons for the management of the Nigerian economy. The established asymmetry in oil price shocks underscores the vulnerability of government revenue and economic stability to global oil market disturbances. In response, policymakers should establish fiscal stabilization funds during periods of high oil prices to help cushion declines in future prices, thus ironing out government expenditure, as well as dampen the adverse effect of adverse shocks. The substantial positive long-term coefficient on capital expenditure (0.210) suggests that government expenditure on infrastructure, education, and health care has significant economic dividends. Therefore, fiscal policy should pay attention to productive capital expenditure instead of intermittent spending in a bid to enhance long-term growth potential. Furthermore, the strong negative correlation between economic growth and inflation (-0.402) underpins the monetary policy imperative role in maintaining price stability. The Central Bank of Nigeria should continue to focus its attention on anti-inflationary measures using responsible monetary policy instruments. As limited diversification in high oil dependency, **structural policies** would encourage the development of non-oil economies, primarily manufacturing and services, to reduce vulnerability to oil price fluctuations. Industrial policies to increase export diversification would improve economic resilience to external shocks. The research contributes to the existing literature by addressing a significant methodological gap in mainstream econometric modeling and providing a more advanced understanding of macroeconomic dynamics in oil-dependent economies, ultimately guiding more powerful evidence-based policy-making in economies faced with sustainable development issues and economic diversification.

Data Availability Statement

This paper uses data from the Central Bank of Nigeria, which can be accessed from 2023 Statistics Bulletin.

Conflict of Interest

The authors declare there is no conflict of interest.

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