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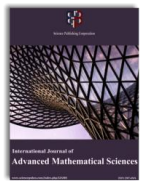

Assessing The Impact of Structural Breaks on Nigeria's GDP: An Application of the SARIMA Model

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Abstract

This study examined the effects of structural breaks on Nigeria's quarterly Gross Domestic Product (GDP) using a Seasonal Autoregressive Integrated Moving Average (SARIMA) modelling framework with intervention analysis. Quarterly real GDP data spanning from 2010 to 2024 were used for the study. Structural breaks were identified through graphical inspection and the Bai–Perron multiple breakpoint test while the Augmented Dickey-Fuller test was used for stationarity assessment. The Bai–Perron multiple break test and model identified two significant structural breaks; comparison across break-adjusted specifications showed that the COVID-19 intervention achieved the lowest AIC (777.72), outperforming the baseline SARIMA model and other structural break specifications. Pulse and step intervention models were evaluated to determine the most suitable representation of the COVID-19 structural break. The pulse intervention model ($\beta = -512.77$, $p < 0.001$) provided a superior fit, demonstrating that the effects of the pandemic's exerted a significant temporary shock rather than a permanent structural shift in Nigeria's GDP. The selected SARIMA$(1,1,1)(1,1,1)_4$ model displayed adequate diagnostic properties with no residual autocorrelation or conditional heteroscedasticity. These findings showed that incorporating structural breaks improved model performance relative to the conventional SARIMA model. The study provides a robust framework for analyzing macroeconomic time series subject to major economic disruptions, providing valuable insights for the formulation of fiscal and monetary policy in Nigeria's vola-tile economic landscape.

Keywords: *Structural Breaks; SARIMA; COVID-19; Intervention Analysis; GDP Forecasting; Diagnostic Properties; Landscape.*

1. Introduction

Gross Domestic Product (GDP) is generally recognized as one of the most crucial indicators of macroeconomic performance because it captures the aggregate value of goods and services produced within an economy over a given period [1]. A robust model that guarantees accurate and reliable GDP forecasts is therefore important for effective economic planning, monetary regulation, fiscal policy formulation, investment decisions, and sustainable development strategies. In developing economies such as Nigeria, an advanced GDP model assumes more significance considering the persistent macroeconomic instability, external shocks, fluctuating oil prices, inflationary pressures, exchange rate volatility, and structural policy transitions that continually transform economic activities [2].

Nigeria's economy has undergone some vital structural transformations over the years. These include the oil boom era of the 1970s, the Structural Adjustment Programme (SAP) introduced in 1986, banking sector reforms in the mid-2000s, the global financial crisis of 2008–2009, the oil price collapse between 2014 and 2016, the 2016 economic recession, the COVID-19 pandemic shock in 2020, and the removal of fuel subsidy in 2023 by the administration of President Bola Ahmed Tinubu. The fuel subsidy removal policy resulted in a substantial rise in transportation costs, energy prices, inflationary pressures, and exchange rate adjustments, thereby creating major macroeconomic disruptions across various Nigerian economic sectors. These events altered the underlying pattern and behavior of key macroeconomic variables, including GDP. Based on a study by [3], structural shifts in macroeconomic time series can cause significant distortion of statistical properties such as stationarity and parameter stability, thereby reducing the predictive performance of conventional forecasting models if such breaks are not considered.

Various econometric and time-series techniques for GDP forecasting models have been adopted by researchers due to the increasing complexity of macroeconomic dynamics. Among these approaches, the Autoregressive Integrated Moving Average (ARIMA) model developed by [4] continues to be one of the most widely utilized forecasting models due to its flexibility and forecasting reliability. However, several

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macroeconomic variables show seasonal patterns because of recurring economic activities, making the Seasonal Autoregressive Integrated Moving Average (SARIMA) model more suitable for capturing both trend and seasonal variations in economic time series.

A number of empirical studies have explored GDP forecasting in Nigeria using ARIMA-class models. [5] applied the ARIMAX model to forecast Nigeria's GDP and discovered that ARIMA-based techniques provide reliable forecasting performance for macroeconomic analysis. Similarly, [6] conducted a study on the performance comparison of regression with ARIMA errors and the conventional ARIMA model in forecasting Nigeria's GDP and concluded that ARIMA-related class of models remain useful tools for economic prediction and policy analysis. In another study, [7] utilized an ARIMA-based approach to forecast Nigeria's GDP using data spanning from 1990 to 2023 and reported satisfactory forecasting performance. [8] used an ARIMA(2,1,1) model to analyze Nigeria's GDP from 1981–2019 but acknowledged its inability to account for "black swan" events like the COVID-19 pandemic. Using a hybrid ARIMA-SVR-MLP model, [9] extended ARIMA applications post-2020, obtaining improved accuracy but at the expense of interpretability. These studies collectively emphasize the need for a parsimonious yet structurally informed model that explicitly accounts for intervention effects and seasonal patterns in Nigeria's quarterly GDP.

Beyond Nigeria, many international studies have also established the reliability and effectiveness of ARIMA and SARIMA models in macroeconomic forecasting. [10] studied a systematic comparison of GDP forecasting techniques in an emerging economy and concluded based on the results obtained that ARIMA-based techniques remained competitive in terms of forecast accuracy and robustness. Besides, macroeconomic forecasting models record better performance when underlying nonlinearities and structural changes are adequately incorporated into the modeling process based on a study conducted by [11].

However, critical gaps exist in the Nigerian context despite the extensive literature on GDP forecasting models. First, many existing studies mainly apply conventional ARIMA models while paying limited attention to seasonal fluctuations contained in GDP data. Failure to take seasonality into account could reduce model efficiency because Nigeria's economy is primarily impacted by recurrent agriculture cycles, trade activities, oil production patterns, and periodic consuming behavior. Second, despite Nigeria's multiple economic shocks over time, a significant percentage of earlier research frequently assumed structural stability in GDP series. However, structural breaks that might alter the statistical behavior of GDP series are frequently produced by macroeconomic shocks and policy changes.

More significantly, a number of previous studies on Nigeria's GDP forecasting models have either completely ignore seasonality or considered structural breaks separately. Studies like [5], [7], [12], [14] for example, mostly concentrated on ARIMA-based forecasting models without specifically addressing the effects of structural breaks within a seasonal forecasting framework. The vulnerability of macroeconomic series to structural breaks was also highlighted by [3], however they neglected to extend the study to GDP forecasting using SARIMA models. Because GDP forecasting in a volatile economy like Nigeria requires a framework that can simultaneously account for seasonal dynamics and structural shifts, this creates a significant vacuum in the literature. Also, a lot of earlier research relied on annual data, which could mask seasonal and short-term fluctuations that are essential for accurate macroeconomic forecasting. The reliability of the current empirical data on Nigeria's GDP models is thus compromised by the inadequate integration of structural break analysis into seasonal time-series models.

Consequently, there is a clear need for a more robust forecasting model that incorporates the realities of structural instability and seasonal economic behavior in Nigeria. This study seeks to address this gap by focusing on modelling Nigeria's GDP under structural breaks using the SARIMA model approach. By integrating the dynamics of seasonality with structural break considerations, the study contributes to the existing literature by providing a more realistic approach to GDP forecasting models in Nigeria's volatile economic environment.

2. Materials and Method

2.1. Study area and data collection

The data used for this study consist of quarterly Gross Domestic Product (GDP) Figs for Nigeria covering the period from 2010 to 2024. The data was obtained from the official statistical database of the Central Bank of Nigeria (CBN), which publishes comprehensive economic and financial time-series series, including real GDP estimates, in its quarterly statistical bulletins and online statistics portal. The quarterly GDP data can be accessed directly from the Central Bank of Nigeria's official website at: https://www.cbn.gov.ng/rates/RealGDP.html All data preprocessing procedures, including data cleaning, data visualization and estimation of model parameters, were carried out using the R statistical software.

2.2. Statistical method

2.2.1. ARIMA model specification

Let $\{Y_t\}$denote a univariate time series (GDP) observed at equally spaced time intervals $t = 1,2, \dots, T$. An ARIMA(p, d, q) model is defined as:

$$\phi(B)(1 - B)^d Y_t = \theta(B)\varepsilon_t, \quad (1)$$

Where:

B is the backshift operator, p is order of autoregressive (AR) component, d is the order of non-seasonal differencing, q is the order of moving average (MA) component, and

$$\varepsilon_t \sim \text{WN}(0, \sigma^2) \quad (2)$$

However, many time series exhibit seasonality, where patterns repeat after a fixed period (e.g., monthly, quarterly, weekly). Standard ARIMA models cannot adequately capture such periodic behavior. To address this, the Seasonal ARIMA (SARIMA) model extends ARIMA by incorporating seasonal autoregressive, differencing, and moving average components.

2.2.2. SARIMA model specification

A SARIMA$(p, d, q)(P, D, Q)_s$ model is defined as:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)\varepsilon_t, \quad (3)$$

Where:
s= seasonal period ($s = 4$ for quarterly data), P, D, Q are seasonal AR, differencing, and MA orders respectively.

2.2.3. Structural break representation

A structural break occurs when the parameters of the data-generating process change at a specific Structural breaks may arise from major economic events such as the 2016 recession, the COVID-19 pandemic (2020Q2), and post-election reforms (2023Q1). More generally, let the GDP series contain $k-1$structural breaks occurring at unknown break dates $\tau_1, \tau_2, \ldots, \tau_{k-1}$ represented as:

$$Y_t = \begin{cases} v_t^{(1)}, & t \le \tau_1 \\ v_t^{(2)}, & \tau_1 < t \le \tau_2 \\ \vdots & \vdots \\ v_t^{(k)}, & t > \tau_{k-1} \end{cases} \quad (4)$$

Where $v_t^{(j)}$denotes the stochastic process governing the j^{th}regime, whose mean, trend, variance, or autoregressive structure may differ across regimes.
Intervention variables are introduced in order to model the identified structural breaks within the SARIMA framework. These interventions could be specified as either pulse or step functions contingent on whether the structural break is temporary or permanent.
This structural variation can be represented using a piecewise specification of the form:
For a pulse intervention,

$$I_{j,t} = \begin{cases} 1, & t = T_j \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Where $T_j$denotes the occurrence of the j^{th}structural break. The pulse intervention captures a temporary shock that affects the series only at the break period.
Similarly, a step intervention is defined as

$$I_{j,t} = \begin{cases} 0, & \text{if } t < T_j, \\ 1, & \text{if } t \ge T_j, \end{cases} \quad (6)$$

Which represents a permanent shift in the level of the series from the structural break point onward.
To incorporate structural breaks, the SARIMA model is extended with intervention variables:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)\varepsilon_t, + \sum_{j=1}^{m} \omega_j I_{j,t} \quad (7)$$

2.2.4. Bai–Perron multiple break test

This tests estimates breaks by minimizing the sum of squared residuals [15-17]:

$$Y_t = x_t'\beta_j + \varepsilon_t, t = T_{j-1} + 1, \ldots, T_j \quad (8)$$

For $j = 1, \ldots, m+1$ regimes, where x_t includes deterministic components, β_j are regime-specific coefficients, and break dates $(T_1, \ldots, T_m)$ are estimated endogenously.
To incorporate structural breaks, the SARIMA model is extended with intervention variables:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \theta(B)\Theta(B^s)\varepsilon_t + \sum_{i=1}^{m} \omega_i I_{i,t} \quad (9)$$

Where:
$I_{i,t}$ = pulse dummy: $I_{i,t} = 1$ if $t = \tau_i$, and 0 otherwise; or step dummy: $I_{i,t} = 1$ if $t \ge \tau_i$, and 0 otherwise
ω_i = magnitude of the intervention effect
For regime-specific parameters, the model can be expressed as:

$$\phi_j(B)\Phi_j(B^s)(1-B)^{d_j}(1-B^s)^{D_j} Y_t = \theta_j(B)\Theta_j(B^s)\varepsilon_t, t \in \text{Regime } j \quad (10)$$

2.2.5. Model comparison

The following specifications are estimated and compared using AIC and BIC:

Model	Description
Baseline	SARIMA without breaks
COVID-19 Only	SARIMA with COVID-19 intervention
Manual Breaks	SARIMA with all historical break dummies
Bai–Perron	SARIMA with statistically determined breaks

The optimal model minimizes information criteria while maintaining satisfactory residual diagnostics (no autocorrelation, normality, homoscedasticity).
This compact section provides the necessary mathematical framework for structural breaks while maintaining focus on the equations and their direct application to your GDP forecasting study.

2.2.6. Augmented Dickey–Fuller (ADF) test model

The Augmented Dickey–Fuller (ADF) test is used to assess stationarity. It examines the null hypothesis of a unit root by estimating a regression of the first-differenced series on its lagged level and lagged differences to account for serial correlation [18-19].
The ADF test is based on the following regression model:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \, \Delta Y_{t-i} + \varepsilon_t \quad (9)$$

Where:
Y_t is the time series under consideration (e.g., quarterly GDP), $\Delta Y_t = Y_t - Y_{t-1}$denotes the first difference of the series, t is a deterministic time trend (optional), α is a constant (drift term), γ is the coefficient associated with the lagged level of the series,k is the number of augmented lag terms, δ_i are coefficients of the lagged first differences, ε_t is a white-noise error term. The hypotheses of the ADF test are stated as:
H_0: $\gamma = 0$ (presence of unit root; series is non stationary
H_1: $\gamma < 0$ series is non-stationary

2.2.7. Identification of ARIMA orders

First-order differencing is applied if a trend exists, which implies that the series is non-stationary:

$$\nabla Y_t = Y_t - Y_{t-1} \quad (10)$$

2.2.8. Seasonal differencing

Seasonal differencing removes repeating seasonal patterns:

$$\nabla_s Y_t = Y_t - Y_{t-s} \quad (11)$$

2.2.9. Identification of seasonal orders

To identify the order of the seasonal component, ACF and PACF at seasonal lags (s, 2s, 3s) are examined; significant spikes at lag ssuggest seasonal components. Seasonal AR is identified by PACF at lag s while Seasonal MA is identified by ACF at lag s,

2.2.10. Model selection criteria

Competing ARIMA and SARIMA models are usually compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQ) [20 - 22], but in this study only AIC and BIC are utilized. The model with the lowest information criterion and satisfactory diagnostics is selected.

3. Analysis

3.1. Presentation of data

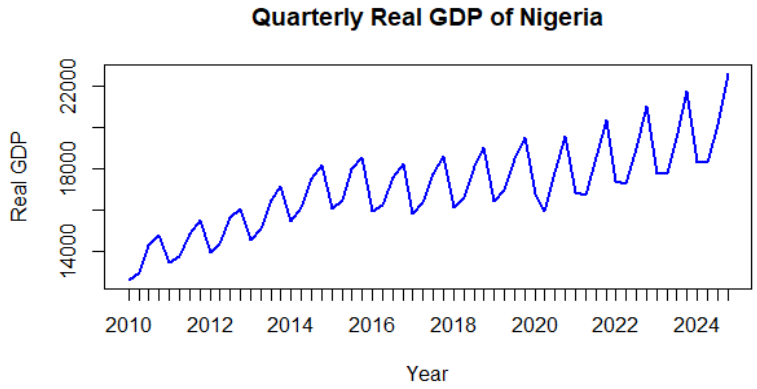

Fig. 1: Original Plots of Nigeria's Quarterly real GDP from 2010 to 2024.

According to Fig. 1, Nigeria's real GDP grew every quarter between 2010 and 2024. However, during significant economic shocks, such as the COVID-19 pandemic, the 2014–2016 oil price crisis, and the post-2023 economic reforms, there were noticeable drops. These sudden shifts suggest the presence of structural breaks in the GDP series.

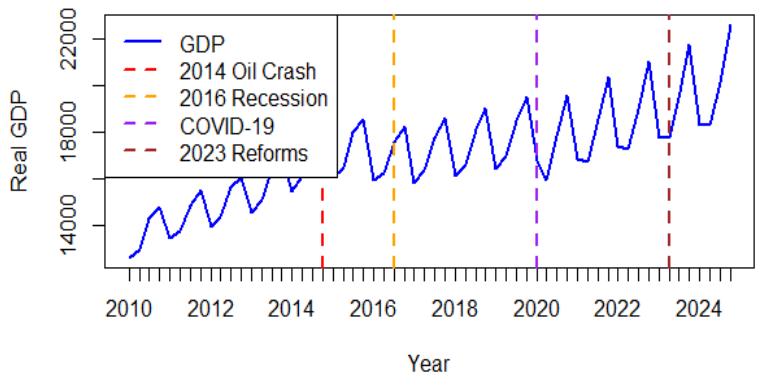

Fig. 2: Plots of Nigeria's Quarterly real GDP with Potential Structural Breaks Based on Major Economic Events.

The possible structural break points in Nigeria's quarterly real GDP are highlighted in Fig. 2, which shows how the series' trend and behavior changed after significant economic events. This demonstrates why structural breaks must be taken into consideration when modeling and projecting GDP.

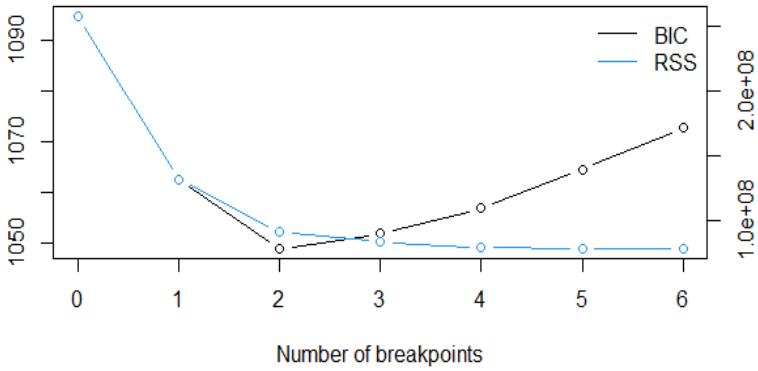

Fig. 3: Bai–Perron Test Results for Structural Break Detection in Nigeria's Quarterly Real GDP.

Fig. 3 shows the structural break points estimated by the Bai–Perron multiple break test. The statistically identified break dates confirm periods where significant changes occurred in the GDP series, providing empirical evidence for incorporating structural breaks into the SARIMA modelling process. There is a decrease in RSS as additional break points are introduced, suggesting improved model fit. However, the BIC reaches its minimum value at two structural breaks, indicating that a two-break model provides the best balance between goodness-of-fit and model complexity. Therefore, the Bai–Perron procedure detects two structural breaks as the optimal specification for Nigeria's quarterly GDP series.

Table 1: Augmented Dickey-Fuller Test for Stationarity

Series	ADF statistics	P-value	Decision
GDP (level)	-1.903	0.614	Non stationary
First difference	-2.440	0.397	Non stationary
Seasonal plus first difference	-4.351	<0.01	Stationary

The Augmented Dickey-Fuller (ADF) test results for stationarity are shown in Table 1. Both the level (ADF = -1.903, p = 0.614) and first difference (ADF = -2.440, p = 0.397) of the GDP series were found to be non-stationary. However, the series became stationary (ADF = -4.351, $p < 0.01$) after both seasonal and first differencing were applied. This suggests that seasonal and non-seasonal differencing were required before fitting the SARIMA model.

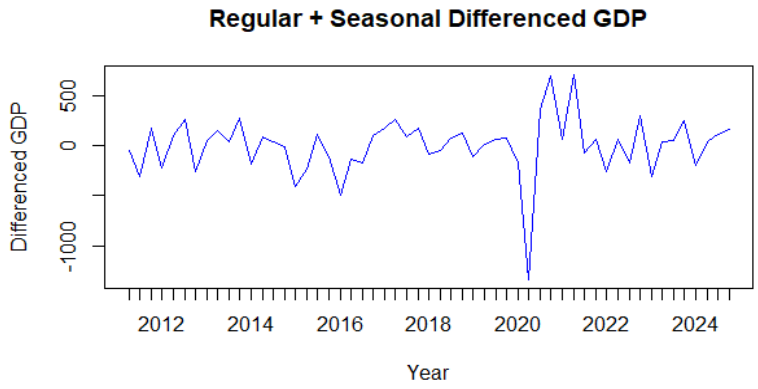

Fig. 4: Plot of Differenced Nigeria's Quarterly GDP Series.

Fig. 4 displays the seasonally and first-differenced GDP series fluctuating around a constant mean with relatively constant variance, confirming that the GDP series is stationary.

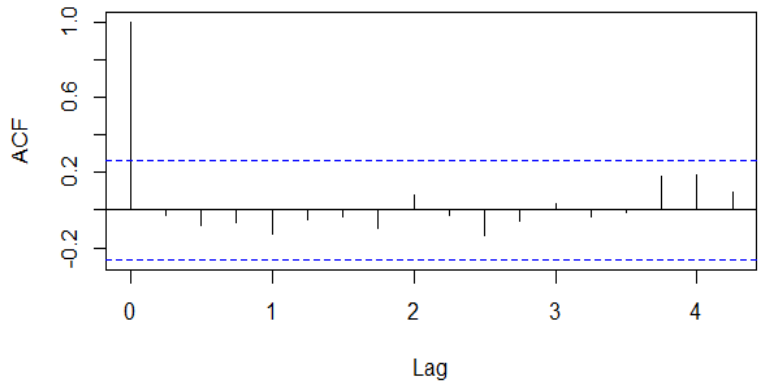

Fig. 5: ACF of Differenced GDP Series.

The ACF plot of the differenced GDP series displays a rapid decay of autocorrelations, demonstrating that the non-stationarity has been successfully removed.

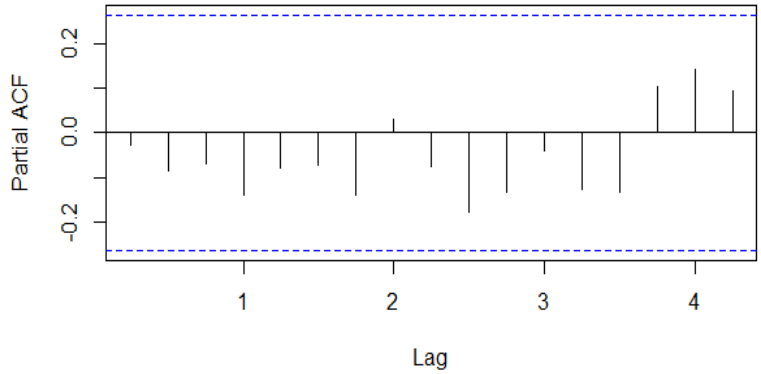

Fig. 6: PACF of the Differenced GDP Series.

A further confirmation of the stationarity of the transformed GDP series was exhibited by the PACF plot, displaying only a few significant spikes followed by a quick cutoff. This clearly supports SARIMA model identification.

Model Identification:

Based on the observations of the ACF and PACF of the stationary GDP series in Figs. 5 and 6, the following models are to be estimated, with the best-performing model selected through the lowest information criterion value rule: SARIMA.$(1,1,1)(1,1,1)_4$, SARIMA$(2,1,1)(1,1,1)_4$, SARIMA$(1,1,2)(1,1,1)_4$], and SARIMA$(2,1,2)(1,1,1)_4$.

Table 2: Model Selection Criteria and Goodness-of-Fit Measures

Model	AIC	BIC	Log-likelihood	σ^2	RSME	MAE	MAPE
$SARIMA(1,1,1)(1,1,1)_4$	784.72	794.76	-387.36	79742.64	260.35	165.15	0.972
$SARIMA(1,1,2)(1,1,1)_4$	786.51	798.55	-387.25	80844.97	259.56	168.03	0.989
$SARIMA(2,1,1)(1,1,1)_4$	786.51	798.55	-387.25	80832.00	259.54	168.07	0.990
$SARIMA(2,1,2)(1,1,1)_4$	788.54	802.59	-387.27	82591.84	259.71	167.73	0.987

Table 2 shows that $SARIMA(1,1,1)(1,1,1)_4$ has the least value of AIC and BIC, hence it surpassed the other proposed models.

Table 2 compares the suspected SARIMA models using information criteria and forecast accuracy measures. The model with the lowest AIC (784.72) and BIC (794.76) [$SARIMA(1,1,1)(1,1,1)_4$] was selected as the best-fitting model, demonstrating superior performance among the competing models.

Table 3: Model Selection Criteria Across Structural Breaks

Rank	Model	AIC	VS Baseline	finding
1	Covid-19 only	777.72	-7.30	Best
2	COVID-19 and 2023 Reform	779.18	-5.53	COVID-19 drives improvement
3	All four manual breaks	782.74	-1.98	Not optimal
4	Baseline Model	784.72	0	Reference point
5	Bai-Perron two Breaks	786.82	+2.10	Higher AIC; no improvement over baseline

The baseline SARIMA model and break-adjusted models are shown in Table 3. The COVID-19 shock had the most effect on Nigeria's GDP series, and the SARIMA model that incorporates only the COVID-19 intervention yielded the lowest AIC (777.72), suggesting that it provided the best fit and that the COVID-19 shock had the greatest effect on Nigeria's GDP series.

Although two structural breakpoints were identified by the Bai–Perron procedure as the optimal segmentation of the GDP series based on the BIC, the corresponding two-break SARIMA specification did not yield the lowest AIC. This is because the breakpoint detection and intervention-model selection evaluate different aspects of the time series. The Bai–Perron procedure detects changes in the underlying data-generating process, whereas the SARIMA-based AIC assesses the overall explanatory adequacy of the fitted models while penalising additional complexity. The lower AIC obtained for the COVID-19-only specification (777.72), compared with the two-break specification (786.82), suggests that the pandemic intervention captured the most significant disruption in the series. Thus, the results distinguish the statistical detection of structural changes from the selection of the most parsimonious intervention model.

Table 4: Evaluation of Pulse and Step Intervention Models for the COVID-19 Structural Break

Intervention Type	Estimate (β)	SE	p-value	AIC
Pulse	-512.7689	118.7074	<0.001	777.42
Step	-540.92	302.74	0.074	787.47

In order to determine whether the pandemic had a temporary or permanent effect on Nigeria's quarterly GDP, pulse and step interventions were evaluated after the selection of the COVID-19 model as the optimal structural break specification. The intervention models were compared using the AIC, estimated intervention coefficient, and statistical significance as given in Table 4. The pulse intervention model attained a lower AIC (777.42) and a statistically significant intervention coefficient ($\beta = -512.77$, $p < 0.001$), whereas the step intervention model had a higher AIC (787.47) and a non-significant coefficient ($\beta = -540.92$, $p = 0.074$). These findings indicate that the COVID-19 impact on Nigeria's quarterly GDP was better characterized as a temporary shock rather than a permanent structural change. Hence, the pulse intervention model was chosen as the final SARIMA intervention model.

Table 5: Parameter Estimation of the Best Fitted Model with COVID-19 Intervention; SARIMA $(1,1,1)(1,1,1)_4$

Parameter	Coeff	STD Error	P-value	sig
AR(1)	0.8052	0.0926	<0.001	----
MA(1)	0.9999	0.0666	<0.001	-----
SAR(1)	-0.6030	0.6687	0.3672	NS
SMA(1)	0.5173	0.7165	0.4703	NS
Covid19 intervention	-512.7689	118.7074	<0.001	-------

The parameter estimates of the selected SARIMA model are presented in Table 5. The non-seasonal AR(1) and MA(1) parameters were statistically significant ($p < 0.001$), while the seasonal AR(1) and MA(1) parameters were not significant, indicating that the short-term dynamics contributed more to the model than the seasonal components. The COVID-19 intervention coefficient (β=−512.77, $p < 0.001$) was statistically significant and negative, suggesting that the pandemic caused a significant temporary negative shock to Nigeria's quarterly GDP series that was greater than what could be explained by autocorrelation, seasonal variation, and the underlying trend. This result demonstrates that accounting for the COVID-19 structural break significantly improves the SARIMA model.

Table 6: Diagnostic Test for the Selected model; SARIMA $(1.1,1)\ (1,1,1)_4$

Test	Statistics	P-value	Conclusion
Ljung-BOX (LAG=8)	$X^2 = 0.6128$	0.6333	No autocorrelation
Shapilo-Wilk	$W = 0.959$	0.0408	Residuals deviate slightly from normality.
ARCH(lag=8)	$X^2 = 3.876$	0.423	No conditional heteroscedasticity

The diagnostic findings for the chosen model are shown in Table 6. Although the Shapiro–Wilk test indicates a slight departure from normality ($p = 0.0408$), the residuals showed no significant autocorrelation and exhibited no evidence of conditional heteroscedasticity. This indicates that the fitted SARIMA model adequately satisfied the model assumptions. Nevertheless, the observed departure from normality may affect the nominal coverage of conventional normality-based confidence intervals and prediction bounds, but the model's point forecasts and captured temporal dependence remain informative.

The break-adjusted $\text{SARIMA}(1,1,1)(1,1,1)_4$ model is written as

$$(1-\phi_1 B)(1-\Phi_1 B^4)(1-B)(1-B^4)Y_t = \beta D_t + (1+\theta_1 B)(1+\Theta_1 B^4)\varepsilon_t, \tag{12}$$

Where

D_t is the structural break variable, β measures the impact of the structural break on GDP.

Since the study's best model includes only the COVID-19 break, D_t is defined as given below

$$D_t = \begin{cases} 1, & \text{only during the COVID} - 19 \text{ shock quarter} \\ 0, & \text{otherwise} \end{cases}$$

Substituting the model coefficients,

$$(1-0.8052B)(1+0.6030B^4)(1-B)(1-B^4)Y_t = -512.7689D_t + (1-0.9999B)(1+0.5173B^4)\varepsilon_t. \tag{13}$$

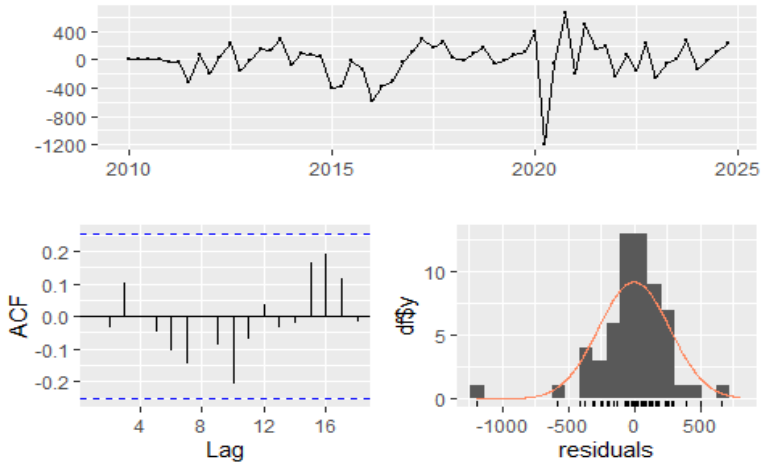

Fig. 7: Residual Diagnostics Plots of the Final $\text{SARIMA}(1,1,1)(1,1,1)_4$ Intervention Model.

Fig. 7 displays the residual diagnostics for the selected final COVID-19 break-adjusted SARIMA$(1,1,1)(1,1,1)_4$ model. The residuals fluctuate randomly around zero without any obvious trend or seasonal pattern. There was no significant autocorrelation in the residual autocorrelation function, confirming that the residuals behave as white noise. Although the distribution of residuals exhibits slight deviation from normality due to a few extreme observations, the overall diagnostic evidence, alongside the Ljung–Box and ARCH test results, strongly indicates that the model adequately captures the dynamics of Nigeria's quarterly GDP.

4. Findings

The study utilized SARIMA models with intervention analysis to examine the impact of structural breaks on Nigeria's quarterly GDP. The findings show that significant economic events were associated with structural changes in Nigeria's GDP series, which supports the inclusion of intervention variables in the SARIMA framework. This finding is in line with [13], emphasizing the vulnerability of macroeconomic time series to structural shifts and the necessity of taking these breaks into account for reliable modeling and inference.

The unit root analysis showed that the GDP series was non-stationary at level but became stationary after regular and seasonal differencing, satisfying the assumptions required for SARIMA modelling. This confirms the importance of transforming macroeconomic time series before model estimation to avoid spurious results, as recommended in the Box–Jenkins methodology and applied in previous studies [12], [14]. The GDP series was non-stationary at level, based on the outcome of the unit root test, but it became stationary following regular and seasonal differencing, supporting the requirements for the SARIMA modeling framework. This confirms the Box–Jenkins methodology's recommendation to modify macroeconomic time series prior to model estimation in order to prevent spurious results [4].

The SARIMA$(1,1,1)(1,1,1)_4$ model adequately captured the stochastic behaviour of Nigeria's quarterly GDP among all the competing model specifications. Furthermore, integrating structural break information improved model performance relative to the conventional SARIMA model, demonstrating that ignoring structural changes may lead to model misspecification. The conclusion that intervention analysis improves the modelling of economic time series influenced by key external events is in line with previous related studies [23 - 25]. The pulse intervention provided a better fit than the step intervention when other intervention specifications were compared. This indicates that the economic impact of the COVID-19 pandemic is better described as a temporary shock rather than a long-term change in the GDP process. This view is in line with Box and Tiao's intervention analysis theory, which states that step interventions reflect long-term level changes whereas pulse interventions capture temporary disruptions. After adjusting for trend, seasonality, and serial dependence, the estimated COVID-19 intervention coefficient was statistically significant, confirming that the pandemic had a quantifiable impact on Nigeria's quarterly GDP. This finding is consistent with an empirical study by [26]. This demonstrates that COVID-19 significantly disrupted economic and other time-series processes, requiring specific modeling of the intervention rather than considering it as random noise. Lastly, the diagnostic tests showed no evidence of conditional heteroscedasticity or residual autocorrelation. This indicates that the chosen SARIMA intervention model adequately reflected the underlying dynamics of Nigeria's quarterly GDP. As a result, incorporating structural breaks produces a GDP series representation that was both statistically adequate and economically significant

5. Conclusion

The importance of accounting for structural breaks in SARIMA modelling of Nigeria's quarterly Gross Domestic Product (GDP) was demonstrated by this study. The study established that accounting for major economic disruptions produces a more robust representation of the GDP series than conventional SARIMA models that assume parameter stability using Box–Jenkins methodology. The empirical evidence indicates that the COVID-19 pandemic was best characterised as a temporary economic shock rather than a permanent structural shift, highlighting the dynamic nature of Nigeria's macroeconomic environment. These findings underscore the need for policymakers and researchers to explicitly capture structural changes when modelling macroeconomic time series, as failure to do so may lead to model misspecification and misleading inferences. The SARIMA model with structural breaks developed in this study can serve as a reliable tool for forecasting Nigeria's GDP while explicitly accounting for the effects of major structural changes in the economy. Future research may extend this framework by integrating multivariate approaches or nonlinear time-series models to account for the complex interactions between macroeconomic indicators and structural shocks.

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Conflict of Interest

The authors declare that there is no conflict of interest.

Authors Contribution

The first author conceptualized and designed the study, performed the analysis, and wrote the original draft. Other authors reviewed and edited the manuscript. All authors read and approved the final manuscript revision and agreed to be accountable for all aspects of the work.

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