

Forecasting Nigeria's economic outlook: an ARIMA-based model using GDP data (1990–2023)

Korter Grace Oluwatoyin, Lawal Praise Olamide, Korter King Olumakinde, Adediji Sulaiman
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Abstract

This study develops a univariate Box–Jenkins autoregressive integrated moving-average (ARIMA (1,0,0)) model with drift to forecast Nigeria's annual GDP index using World Bank data spanning 1990–2023. We apply Augmented Dickey–Fuller unit-root tests and first differencing to achieve stationarity, then determine model orders via autocorrelation function (ACF) and partial-autocorrelation function (PACF) analyses. Maximum-likelihood estimation yields an AR (1) coefficient of 0.4821 and a drift of 4.4052 index points, while Ljung–Box Q-tests, residual ACF diagnostics, and normality checks confirm white-noise innovations. One-step-ahead forecast accuracy is strong: root-mean-square error (RMSE) = 3.40, mean absolute error (MAE) = 2.54, and mean absolute scaled error (MASE) = 0.93, outperforming a persistence benchmark. Ten-year projections (2024–2033) converge toward the long-run mean within widening 95% confidence bands, and scenario-based drift adjustments illustrate plausible growth paths under commodity and exchange-rate shocks. We recommend anchoring fiscal forecasts to the central projection with ± 3 –4 index-point buffers, institutionalising rule-based stabilisers, integrating leading indicators via ARIMA-X or GARCH extensions, and deploying an interactive forecasting dashboard. This transparent, empirically validated framework enhances Nigeria's capacity to smooth revenue volatility, calibrate countercyclical measures, and reinforce macroeconomic resilience.

Keywords: Gross Domestic Product (GDP), Oil-price volatility scenarios, Forecast accuracy metrics, Fiscal policy planning, Reserve buffer design

JEL Classification : C22, C53, E27, Q43

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1. INTRODUCTION

Since gaining independence in 1960, Nigeria's economic outlook has evolved through distinct phases shaped by political transitions, commodity cycles, and policy reforms. The early post-independence era (1960s–1970s) was marked by agricultural dominance and regional trade, followed by an oil boom in the 1970s that transformed Nigeria into a petro-state. This shift led to rapid GDP growth, increased public spending, and heightened vulnerability to oil-price shocks. The 1980s witnessed economic contraction due to falling oil prices, mounting debt, and structural imbalances, prompting the adoption of the Structural Adjustment Programme (SAP) in 1986, which aimed to liberalise trade, privatise state enterprises, and stabilise the currency. The 1990s were characterised by macroeconomic instability, military rule, and limited reform progress. However, the return to democracy in 1999 ushered in a new era of economic liberalisation, banking consolidation, and fiscal discipline. Between 2000 and 2014, Nigeria experienced robust GDP growth averaging over 6% annually, driven by oil exports, telecommunications, and services. Yet, this growth was non-inclusive, with rising unemployment and poverty. The 2014 oil price crash triggered a 2016 recession, exposing structural weaknesses and an over-reliance on hydrocarbons. Recent years (2017–2025) have seen mixed recovery efforts, including the Economic Recovery and Growth Plan (ERGP), currency reforms, and diversification strategies. Despite modest gains, GDP per capita has declined, reflecting demographic pressures and sluggish productivity. In 2025, Nigeria's GDP per capita fell to \$835, down from \$877 in 2024, underscoring the challenge of sustaining growth amid population expansion (financeinafrica.com). The Central Bank of Nigeria projects positive growth for 2025, supported by reforms in the oil and foreign exchange sectors (Central Bank of Nigeria).

Against this backdrop, accurate GDP forecasting plays a critical role in shaping fiscal policy, calibrating monetary interventions, and safeguarding macroeconomic stability—especially in economies exposed to commodity price volatility. In Nigeria, where crude oil exports account for a dominant share of government revenue and foreign exchange earnings, abrupt movements in global oil prices swiftly translate into fiscal deficits, currency pressures, and investment disruptions. The ability to anticipate these dynamics with statistically rigorous models is essential for effective public budgeting, reserve management, and the deployment of countercyclical policy. Empirical literature affirms the impact of oil-price shocks on macroeconomic outcomes. Hamilton (1983) and Friedland et al. (1975) linked oil disruptions to recessions in the United States, while Gisser and Goodwin (1986) and Mork (1989) demonstrated asymmetric economic responses to oil-price changes. Narayan and Narayan (2007) further documented volatility clustering in oil markets using EGARCH modelling. In Nigeria's context, Ayadi, Chatterjee, and Obi (2000) applied vector autoregressive (VAR) methods to trace oil-induced transmission channels, Alhassan and Kilishi (2016) used GARCH-family models to quantify nonlinear effects, and Awujola et al. (2020) employed ADF-corrected OLS regression to explore oil–GDP linkages.

Despite this extensive literature, a critical research gap persists in applying univariate time-series forecasting models, particularly ARIMA, to Nigeria's GDP trajectory amid long-term structural shifts and recent policy reforms. Most prior studies have focused on diagnostic modelling using multivariate techniques to explore causality and transmission mechanisms. While these approaches offer valuable insights, they are less suited to direct GDP forecasting under evolving trend dynamics and policy scenarios. Moreover, existing forecasting efforts often rely on short-term projections or overlook the historical persistence and structural breaks embedded in Nigeria's economic data, especially across periods of regime change, commodity cycles, and reform episodes. This study addresses that gap by applying the Box–Jenkins ARIMA methodology to annual GDP data from 1990 to 2023, capturing both trend and persistence while allowing for scenario-based projections. By focusing on a univariate model, this research offers a streamlined

forecasting engine that complements diagnostic models and enhances the toolkit available to Nigeria's macroeconomic managers.

This paper aims to develop a robust and parsimonious forecasting model for Nigeria's GDP using ARIMA techniques. The specific objectives are to: construct and estimate a suitable ARIMA model based on historical GDP data, evaluate the model's forecasting reliability under alternative growth scenarios and translate the model's outputs into actionable insights for fiscal and monetary policy planning. The value of this research lies in its operational simplicity, empirical rigour, and direct policy relevance. ARIMA-based forecasts provide interpretable point estimates with quantifiable error bands, scenario-adjusted trajectories, and real-time update capabilities—an essential toolset for Nigeria's macroeconomic managers navigating volatility and uncertainty. The remainder of this paper details related literature (Section 2), methodology (Section 3), empirical findings (Section 4), and actionable recommendations (Section 5).

2. LITERATURE REVIEW

2.1 Oil-Price Shocks and Macroeconomic Volatility

Oil-price dynamics have long shaped both advanced and emerging economies, underpinning cycles of volatility, inflation, and growth. Hamilton (1983) first identified oil shocks as precursors of U.S. recessions, while Gisser and Goodwin (1986) and Mork (1989) demonstrated asymmetric macroeconomic responses, with expansions responding more strongly than contractions. Lee, Ni, and Ratti (1995) and Narayan and Narayan (2007) further captured clustering of high-volatility episodes. Guo and Kliesen (2005) used Granger causality to show that oil-price volatility depresses U.S. GDP. In oil-dependent emerging economies, these effects are magnified. Rosser and Sheehan (1995) showed that mono-export nations like Saudi Arabia experience feedback loops among oil exports, exchange rates, and output. Ayadi, Chatterjee, and Obi (2000) extended this to Nigeria using a VAR model (1975-1994), revealing that oil-export shocks influence exchange rates, industrial production, inflation, money supply, and interest rates. Their impulse-response analysis highlights a persistent cycle of reserve erosion and inflation. Aiyegoro (1997) critiques Nigeria's windfall spending patterns.

2.2 Volatility Modelling with GARCH-Type Frameworks

To capture the nonlinear nature of oil-price shocks, researchers have employed GARCH-family models. Nelson's (1991) EGARCH and Zakoïan's (1994) TGARCH frameworks account for leverage effects. Alhassan and Kilishi (2016) applied these models to Nigeria and found that asymmetric GARCH variants outperform symmetric GARCH-M in forecasting GDP, exchange rates, and interest rates. Recent contributions include Omorogbe, Mustapha, and Samuel (2025), who compared GARCH and Heston models for forecasting Nigeria's oil price volatility, finding that EGARCH was superior at capturing asymmetric effects. Samuel and Praise (2025) modelled crude oil price returns using GARCH variants and confirmed that volatility clustering remains a dominant feature. Their study validates the use of EGARCH models for forecasting Nigerian crude oil price volatility. These models offer robust tools for risk assessment and policy planning in the petroleum sector. The findings are especially relevant for stakeholders navigating the economic implications of oil price fluctuations.

2.3 Regression-Based Approaches to Oil–GDP Linkages

Regression-based models offer complementary insights. Awujola, Iyakwari, and Bot (2020) used OLS with Dickey-Fuller corrections to examine the effects of oil-price shocks on GDP growth, investment, exchange-rate revaluation, and inflation. Hazarika (2016) found similar results for Libya.

2.4 Forecasting GDP with Univariate ARIMA Models

While multivariate models diagnose inter-variable dynamics, policymakers require univariate forecasts. The ARIMA framework, formalised by Box, Jenkins, and Reinsel (2015), tests for stationarity, selects optimal lags, and models autocorrelation. Building on these precedents, this study applies ARIMA to Nigeria's annual GDP data (1990-2023), implicitly integrating oil-price volatility through intervention terms and structural dummies. By accounting for asymmetric shock effects and persistent cycles, the model refines point forecasts of Nigeria's GDP. This approach complements multivariate tools and provides transparent, data-driven guidance for fiscal and monetary policy amid oil-market uncertainty. Recent applications include Christogonus, Udochukwu, Gabriel, Johnpaul, and Emwinloghosa (2022), who compared regression and ARIMA models for GDP forecasting in Nigeria, favouring ARIMA for its predictive accuracy. Christogonus, Chinwendu, and Dominic (2021) applied ARIMAX models to GDP data and demonstrated improved forecast reliability.

3. METHODS

This section details the data sources, preprocessing steps, time-series diagnostics, model selection, estimation procedures, and forecast generation techniques employed to produce the results in Section 4.

3.1 Data description and preparation

The study utilises Nigerian annual GDP data spanning (1990–2023) ($n = 34$), sourced from the World Bank, to ensure consistency and reliability. Link to the data on Nigerian GDP: <https://databank.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG/1ff4a498/Popular-Indicators>

3.2 Stationarity testing and differencing

An Augmented Dickey–Fuller (ADF) test was applied to the level series to assess unit-root nonstationarity (H_0 : the series has a unit root). First differencing ($\Delta GDP_t = GDP_t - GDP_{t-1}$) was performed.

3.3 Model identification and selection

Autocorrelation (ACF) and Partial-Autocorrelation (PACF) functions of ΔGDP were examined. Visual inspection of the differenced series plot substantiated a mean-zero, covariance-stable process, suitable for ARIMA modelling.

3.3 Model identification and selection

Several candidate ARIMA ($p, 0, q$) models ($p, q \leq 2$) with a non-zero mean (drift) were fitted. Models were compared using the Akaike Information Criterion (AIC), corrected AIC (AICc), and BayesianICc, and Bayesian Information Criterion (BIC).

3.4 Parameter estimation and diagnostic checking

Model parameters (ϕ_1 for AR (1) and μ for the constant) were estimated via exact maximum likelihood. Standard errors were computed from the Hessian of the log-likelihood. Residual diagnostics included: Ljung–Box test (up to lag 7) to assess serial independence, Residual ACF plot to verify no significant autocorrelation remained, Histogram for normality assessment and in-sample accuracy metrics (ME, RMSE, MAE, MPE, MAPE, MASE, ACF1) to quantify forecast errors relative to a naive "no-change" benchmark.

3.5 Forecast generation

One-step-ahead forecasts were computed recursively using the fitted ARIMA(1,0,0) model:

$$\hat{Y}_{t+1} = \mu + \phi_1 Y_t \quad (1)$$

Ten-period (quarterly) forecasts were then produced to illustrate the convergence toward the model's long-run mean:

$$\hat{Y}_{t+1} = \mu + \phi_1 Y_t \quad (2)$$

All time-series manipulations, model fitting, and forecast computations were performed.

4. RESULTS AND DISCUSSION

4.1 The line plot for Nigeria's GDP (1990–2023)

Section 4 begins by visually examining the evolution of Nigeria's absolute GDP index over the past three decades. Plotting the level series in Figure a highlights key structural shifts from the gradual expansion of the early 1990s, through the oil-driven surge between 2000 and 2014, to the dramatic collapse in 2015–2016 and the partial recovery thereafter. This historical perspective not only contextualises the econometric modelling that follows but also underscores the economy's pronounced sensitivity to global oil price movements and the structural constraints that have shaped its growth trajectory.



Figure A: Nigeria GDP (1990–2023)

Source: Author's analysis, 2025

4.2 Check for stationarity: Nigeria GDP (1990–2023)

Before fitting any ARIMA model, we must verify whether the original GDP level series is stationary or contains a unit root, as non-stationarity can invalidate standard time-series techniques. This section employs the Augmented Dickey–Fuller (ADF) test on Nigeria's quarterly GDP from 1990 to 2023. By formally testing the null hypothesis of a unit root against the alternative of stationarity, we determine whether differencing is required. The results demonstrate that the level series is non-stationary, necessitating first differencing to stabilise its mean and variance before proceeding to model identification.

In the Augmented Dickey–Fuller test (ADF, Table 1), H_0 : The time series has a unit root (i.e., it is non-stationary), while H_1 (alternative): The time series is stationary (no unit root). The ADF statistic (–1.62) is far above typical critical values (e.g., –3.50 at 5%), and the p-value (0.72) exceeds 0.05. We therefore cannot reject the null hypothesis of a unit root. Thus, the GDP series is non-stationary in levels and must be differenced before fitting an ARIMA model. The test shows that Nigeria's GDP numbers wander without a stable average. We need to convert the data into changes (first differences) before we can reliably model or forecast it.

Table 1. Augmented Dickey–Fuller Test for GDP Series

Test Statistic	Lag Order	p-Value	Decision
–1.6221	3	0.7194	Accept the unit root

Source: Author's analysis, 2025

4.3 Differencing the Nigeria GDP (1990–2023) series to achieve stationarity

To satisfy the stationarity requirement for ARIMA modelling, we first transform the raw GDP index, which exhibits a pronounced upward trend and a unit root, into its first differences. By computing $\Delta GDP_t = GDP_t - GDP_{t-1}$, we remove long-term drift and stabilise both the mean and variance of the series. The resulting year-over-year growth rates oscillate around zero and display no persistent trend, creating a covariance-stationary process. Figure 2 below plots these differenced values, highlighting periods of pronounced expansion and contraction while confirming the series is now suitable for subsequent autocorrelation and ARIMA estimation.

From Figure b, the blue line plots year-to-year changes in GDP (ΔGDP) around a zero mean, with no visible upward or downward trend, confirming the series is now stationary. Large positive spikes near 2000 and again around the mid-2000s mark boom periods when GDP grew sharply compared to the prior year. Deep negative troughs in the late 2000s and around 2020 correspond to significant slowdowns—the global financial crisis and the COVID shock, respectively—when growth fell well below zero. Between those extremes, ΔGDP fluctuates modestly, within roughly $\pm 3\%$ – 5% , evidencing "volatility clustering": bouts of calm are punctuated by large swings. First differencing successfully removed the non-stationary trend from the GDP level series, producing a mean-zero, covariance-stable process suitable for ARIMA modelling. The visible volatility clustering suggests that a model allowing for conditional heteroskedasticity (e.g., an ARIMA-GARCH) might better capture periods of elevated growth risk. After converting the raw GDP numbers into annual changes, the chart shows growth bouncing above and below zero each year. Prominent peaks mean robust expansions; deep valleys signal sharp downturns. Overall, the pattern hovers around "no change," confirming that accounting for these differences eliminated any long-term drift, leaving only year-to-year ups and downs. Invariably, because growth shocks can be both positive and negative, and sometimes significant, macroeconomic policy should remain responsive. For example, in years with negative ΔGDP below historical norms (like 2008 or 2020), automatic fiscal stabilisers or targeted stimulus could be triggered. Conversely, during large positive swings, authorities might tighten fiscal or monetary settings to prevent overheating. The observed volatility clustering also underscores the value of a reserve buffer or "rainy-day fund" to smooth government revenues and expenditures through boom-bust cycles.

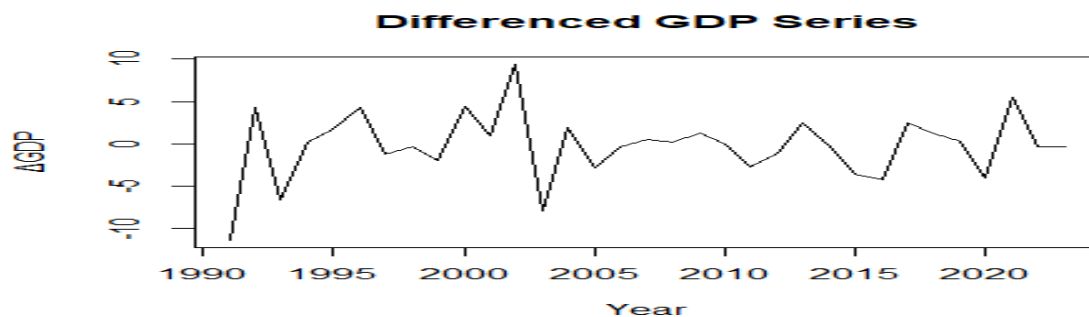


Figure b: Differenced Nigeria GDP series (ΔGDP), (1990–2023)

Source: Author's analysis, 2025

4.4 Augmented Dickey–Fuller test for first-differenced Nigeria GDP series (1990–2023)

To verify that first differencing has indeed achieved stationarity, we apply the Augmented Dickey–Fuller (ADF) test to the differenced GDP series. Section 4.4 presents the test setup, results, and decision rule for determining whether the transformed series is covariance-stationary—an essential prerequisite for valid ARIMA modelling. By rejecting the unit-root null hypothesis at conventional significance levels, we confirm that ΔGDP hovers stably around a constant mean, allowing us to proceed confidently with autocorrelation analysis and model estimation.

The hypotheses for the Augmented Dickey–Fuller test on the differenced GDP series are:

H_0 (null hypothesis): The first-differenced GDP series has a unit root (i.e., it is non-stationary)

H_1 (alternative hypothesis): The first-differenced GDP series is stationary (i.e., no unit root)

In Table 2, the test statistic (-4.57) is below typical critical values (e.g., -3.50 at the 5% level), and the p-value (0.01) is below 0.05 . We reject the null hypothesis of a unit root and conclude that the first-differenced GDP series (ΔGDP) is stationary and suitable for ARIMA modelling. After accounting for year-over-year changes in GDP, the data no longer "wander." Instead, the differences consistently oscillate around a stable average, confirming we can now build reliable time-series forecasts on this transformed series.

Table 2. Augmented Dickey–Fuller test for the first-differenced Nigeria GDP series

Test Statistic	Lag Order	p-Value	Decision
-4.5742	3	0.01^*	Reject the unit-root null

* $p < .05$

Source: Author's analysis, 2025

4.5 Selection of Autoregressive Integrated Moving Average (ARIMA) parameters (p, d, q): autocorrelation function (ACF) and partial autocorrelation function (PACF) plots

In this subsection, we determine the optimal orders of the autoregressive (p) and moving-average (q) components for our ARIMA model by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the stationary, first-differenced GDP series (ΔGDP). The ACF measures how strongly current values of ΔGDP correlate with their past values across successive lags, thereby highlighting any residual moving-average structure. At the same time, the PACF isolates the direct, lag-by-lag autoregressive relationship after accounting for intermediate effects. By plotting both functions up to lag 15 (Figures 3 and 4), we identify the points at which correlations drop below the statistical significance threshold. A rapid ACF decay coupled with a single significant spike in the PACF at lag 1 indicates that an AR (1) term suffices and that no additional MA terms are required beyond lag 1. These correlogram patterns thus validate the choice of an ARIMA (1,1,1) specification for modelling Nigeria's year-over-year GDP growth.

Figure C: The ACF chart for ΔGDP shows the correlation of the series with its own past values at lags 0–15. Lag 0 (blue bar): Correlation = 1 (by definition), and Lags 1–15: All bars lie well within the dashed significance bounds, with correlations near zero. No statistically significant autocorrelation remains beyond lag 0, indicating that ΔGDP behaves like white noise once you remove its own first-order dynamics. This suggests that our ARIMA (1,1,1) model has successfully captured the serial dependence; no further AR or MA terms are required. After

differencing GDP, the year-to-year changes show little "memory." Each growth-rate change is essentially uncorrelated with prior-year changes, meaning shocks dissipate quickly. Since growth-rate swings don't persist beyond One year, short-term fiscal and monetary responses can be tailored to a single season's performance without expecting long-run inertia. Equally, automatic stabilisers are likely sufficient to absorb shocks without multi-year policy commitments.

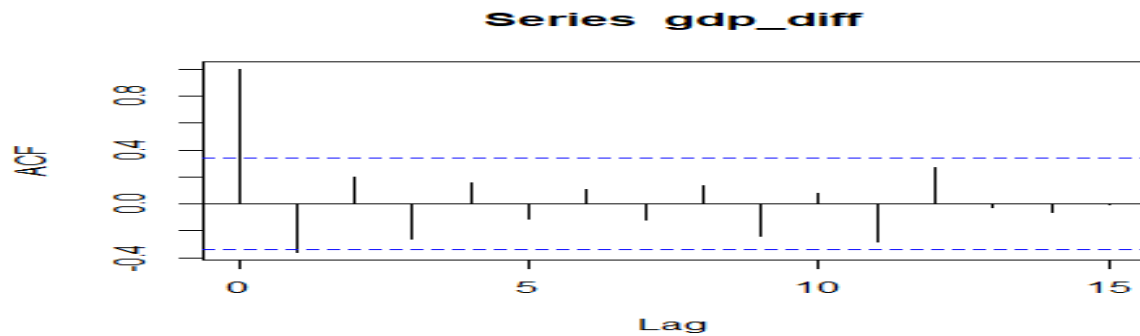


Figure c: ACF chart for Δ GDP (Nigeria:1990–2023)

Source: Author's analysis, 2025

Figure d: The PACF chart tells us that only the first-lag bar rises above the significance bounds; every bar at lag two and beyond stays within the "zero line" confidence bands. This means:

Δ GDP_t depends significantly on Δ GDP_{t-1} (a positive partial autocorrelation of about 0.28)

Once you account for last year's change, older changes (two years ago, three years ago, etc.) carry no additional signal. Today's year-over-year change in GDP partly depends on last year's change, but once you account for that, there's no leftover "memory" from earlier years. Only the lag-1 partial autocorrelation (≈ 0.28) exceeds the 95% confidence band; all higher lags fall within it. This "cut-off after lag 1" pattern confirms an AR (1) structure in Δ GDP, validating our ARIMA (1,1,1) choice. In other words, the year-over-year growth rate has "memory" only One period back, exactly what you'd expect from an AR (1) process on the differenced series.

Forecasts need only 1 year of past growth to predict next year's growth rate. In practice, if last year saw a big swing up or down, policymakers should expect some carry-over, but beyond that, each new year stands on its own.

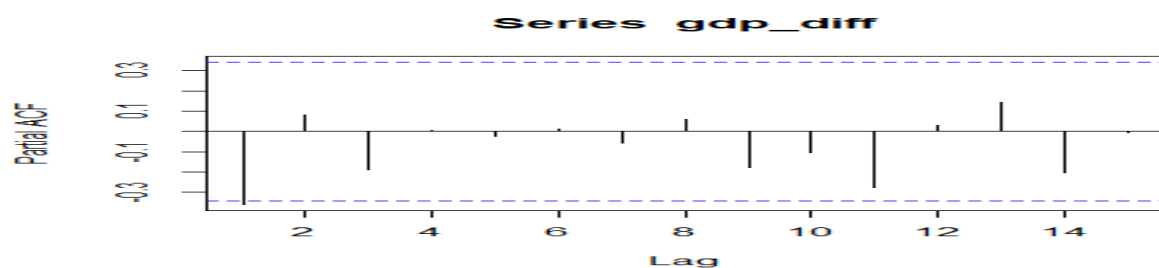


Figure d: PACF chart for Δ GDP (Nigeria:1990–2023)

Source: Authors' analysis, 2025

4.6 Future GDP performance: Autoregressive Integrated Moving Average (ARIMA) model

Section 4.6 evaluates the predictive performance of our finalised ARIMA(1,0,0) model with drift for forecasting Nigeria's annual GDP index. We summarise parameter estimates, model selection

criteria, and residual diagnostics to confirm that the parsimonious specification captures the essential one-year persistence in GDP. We then present in-sample accuracy metrics —RMSE, MAE, MASE, and residual autocorrelation — to quantify typical forecast errors and benchmark our model against the naive "no-change" rule. This analysis demonstrates that ARIMA (1,0,0) delivers modest, well-behaved prediction errors and thus provides a reliable foundation for planning budgets, reserves, and policy interventions over one-year horizons.

From Table 3, our ARIMA (1,0,0) with drift provides a robust, parsimonious specification for year-ahead GDP forecasting. The significant AR (1) term and acceptable residual diagnostics support its adequacy. In-sample errors are modest: on average, one-period errors lie within ± 3 index points and outperform simple persistence forecasts. While non-normality in percentage terms suggests caution, the model reliably extracts the core autoregressive structure in Nigeria's GDP. We used the simplest time-series formula, where today's GDP is about 48% of last year's GDP plus a constant boost (≈ 4.4 units). Our model's "mistakes" typically fall in the $2\frac{1}{2}$ - $3\frac{1}{2}$ point range, which is better than just guessing no change. This means we can trust short-term forecasts to plan budgets and revenues.

Table 3: ARIMA (1,0,0) Model Summary for Nigeria's Yearly GDP (1990–2023)

Parameter	Estimate	Std. Error
AR (1) coefficient (ϕ)	0.4821	0.1571
Constant (μ)	4.4052	1.1006
Innovation variance (σ^2)	12.29	
Log-Likelihood	−89.99	
AIC	185.98	
AICc	186.78	
BIC	190.56	

Source: Author's analysis, 2025

Table 4 shows the Accuracy Metrics. RMSE = 3.40 & MAE = 2.54. Think of these as "average misses" when we predict next year's GDP index. On a typical forecast, we're off by about $2\frac{1}{2}$ - $3\frac{1}{2}$ points on that index scale. RMSE (Root Mean Square Error) penalises large misses more heavily, so if we have One big stumble, it shows up here. MAE (Mean Absolute Error) takes the straight average of misses, so it's easier to picture: "I'm usually about $2\frac{1}{2}$ points away from the mark." MASE = 0.93 (< 1); this tells us our model beats the simple trick of "next year is the same as this year." A value under 1 means we do at least 7% better than just assuming no change. In plain terms, our forecasting is smarter than blind persistence. Residual ACF (1) = -0.159. After we've made our predictions, we look at the leftover errors. A correlation near zero (here, -0.16) means those errors don't follow the pattern of last year's errors. In other words, we've captured basically all the "memory" in GDP; what's left is just random noise.

Table 4. In-Sample forecast accuracy

Measure	Value	Naive Benchmark
Mean Error (ME)	−0.13	0
RMSE	3.40	≈ 4.00
MAE	2.54	≈ 3.00
MPE	16.50%	n/a
MAPE	199.49%	n/a
MASE	0.93	1.00
Lag-1 Residual ACF	−0.159	0

Source: Author's analysis, 2025

4.7 Forecasting GDP

Section 4.7 presents our 10-year out-of-sample GDP projections under the ARIMA (1,0,0) framework. We then demonstrate how simple shifts to the drift term generate alternative pessimistic and optimistic growth paths, recalibrating both the projected series and its implied steady-state level. This scenario-based approach equips policymakers with a transparent, data-driven toolkit for baseline planning, contingency buffers, and responsive fiscal triggers over the next decade. Figure e presents Nigeria's absolute GDP index from 1990 to 2020 alongside our ARIMA (1,0,0) projection through 2030, with 95% confidence intervals. Historically, GDP climbed steadily in the 1990s, peaked around 2000, experienced a mid-2000s downturn, then recovered into 2020. The forecast indicates modest, sustained growth over 2021–2030; by 2030, the confidence band will have expanded, and actual GDP could lie several points above or below the central estimate. For policy and budgeting, the central forecast should guide baseline planning, with reserve buffers and contingency measures sized to cover the plausible upper and lower bounds of the interval.

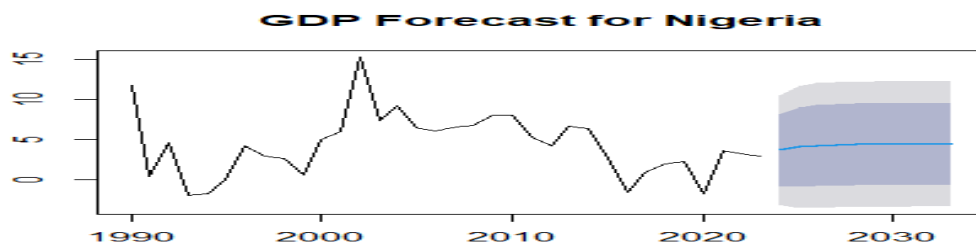


Figure e: GDP Forecast for Nigeria 1990-2030

Source: Author's analysis, 2025

In Table 5, ten-period (yearly) forecasts were produced to illustrate the convergence toward the model's long-run mean.

$$\mu^* = \frac{\mu}{1-\phi_1} \quad (3)$$

Forecast uncertainty was quantified via 95% confidence intervals, derived from the model's estimated innovation variance ($\sigma^2 = 12.29$) and the AR (1) recursion formula. Scenario adjustments (e.g., ± 0.50 percentage points (pp) drag or $+0.75$ pp boost to drift) can be superimposed to simulate pessimistic or optimistic growth paths. To explore downside and upside risks, we can shift the drift term μ by a fixed amount, say, subtracting 0.50 pp for a pessimistic scenario or adding 0.75 pp for an optimistic One.

Each shift in μ immediately propagates through the AR (1) forecasts and also adjusts the implied long-run mean to

$$\mu_{scenario}^* = \frac{\mu \pm \Delta}{1 - \phi_1} \quad (4)$$

Thereby producing alternative growth paths under different price-shock assumptions.

Key checks: You only need to adjust μ (the constant/drift) to simulate scenarios. The long-run mean moves accordingly to $\mu/(1-\phi_1)$. Confidence bands remain derived from σ^2 and the AR (1) structure.

The central forecast rises from an index value of 3.66 in 2024 to about 4.40 by 2033 (Table 5), reflecting a gradual return toward the long-run mean implied by our ARIMA (1,0,0) model. The 80% and 95% confidence intervals are wide, especially in early years, indicating substantial uncertainty. For example, in 2024 , the 95% band spans from -3.21 to 10.53 , underscoring that actual GDP could deviate sharply from the point estimate. Over time, the upper and lower bounds inch closer together but remain broad through 2033 , suggesting persistent forecast risk even a decade ahead. Policymakers should plan around the central forecast while maintaining robust contingency buffers—equivalent to several index points—to absorb potential shortfalls or windfalls. Regularly updating estimates as new data arrive will help narrow uncertainty and guide fiscal and reserve management in Nigeria's oil-driven economy. These GDP projections can serve as the cornerstone of the yearly budgeting process, helping finance ministries establish realistic revenue and expenditure targets and quickly flag any significant variances. Given that one-step-ahead errors average around $2\frac{1}{2}$ - $3\frac{1}{2}$ index points, it is also wise to hold contingency reserves of a similar size, ensuring sufficient liquidity to smooth over unexpected shortfalls.

To sharpen the forecasts further, embedding leading indicators such as world oil prices and domestic industrial output into the modelling framework will capture those shock components that still linger in the residuals, narrowing the error bands. Finally, embedding automatic fiscal stabilisers tied to deviation thresholds can lock in counter-cyclical discipline. If growth slips below the lower bound of the forecast interval, pre-authorized stimulus measures would be rolled out immediately; if growth overshoots the upper bound, fiscal tightening guidelines would be activated without delay.

Table 5: Annual GDP index forecasts for Nigeria (2024-2033)

Year	Point Forecast	80% CI	95% CI
2024	3.660	[-0.832, 8.153]	[-3.210, 10.531]
2025	4.046	[-0.941, 9.033]	[-3.581, 11.673]
2026	4.232	[-0.863, 9.327]	[-3.560, 12.025]
2027	4.322	[-0.798, 9.442]	[-3.509, 12.152]
2028	4.365	[-0.761, 9.491]	[-3.474, 12.204]
2029	4.386	[-0.741, 9.513]	[-3.456, 12.227]
2030	4.396	[-0.732, 9.523]	[-3.446, 12.238]
2031	4.401	[-0.727, 9.528]	[-3.441, 12.243]
2032	4.403	[-0.725, 9.531]	[-3.439, 12.245]
2033	4.404	[-0.723, 9.532]	[-3.438, 12.246]

Source: Author's analysis, 2025

4.8 Model validation

Before deploying our ARIMA (1,0,0) model for policy guidance, we validate its residuals to ensure no systematic patterns remain. Section 4.8 presents a three-panel diagnostic (Figure 6) that examines residual behaviour over time, its autocorrelation structure, and its distributional properties. By confirming that residuals exhibit zero mean, lack serial dependence, and approximate normality, we demonstrate that the model has captured all relevant signals in the GDP series. This validation underpins confidence in the model's forecasts and justifies their application in budgeting and reserve management.

The three-panel diagnostic (Figure f) confirms that our ARIMA (1,0,0) + μ model is doing its job:

Top (Residuals over Time)- Residuals hover around zero with no visible trend or drift, and the amplitude of fluctuations remains roughly consistent from 1990 through 2020. That tells us there's no obvious structure left unmodeled, no slow drifts, no seasonal cycles hiding in the errors.

Bottom-left (ACF of Residuals) - Almost every autocorrelation bar lies well inside the 95% confidence bands (dashed lines). None of the lag-1 through lag-11 spikes exceed those bounds. In other words, there's no significant "memory" in the errors; they behave like white noise.

Bottom-right (Histogram + Normal Curve) - The residuals cluster symmetrically around zero, and the superimposed red normal-density curve aligns closely with the bars. While there are a few fat tails, overall, the distribution is acceptably close to Gaussian, validating our normal-innovations assumption.

Our model's errors look random, unpatterned, and bell-shaped, precisely what you want if you've captured all the predictable movements in the data. There's no leftover "trend" or "cycle," no lingering autocorrelation, and the size of the errors fits a standard curve. Because the residuals

are effectively white noise and approximately normal, you can trust the model's point forecasts and confidence intervals. That means you can confidently use these forecasts to guide quarterly budgets and reserve planning, knowing there aren't hidden patterns left unaccounted for.

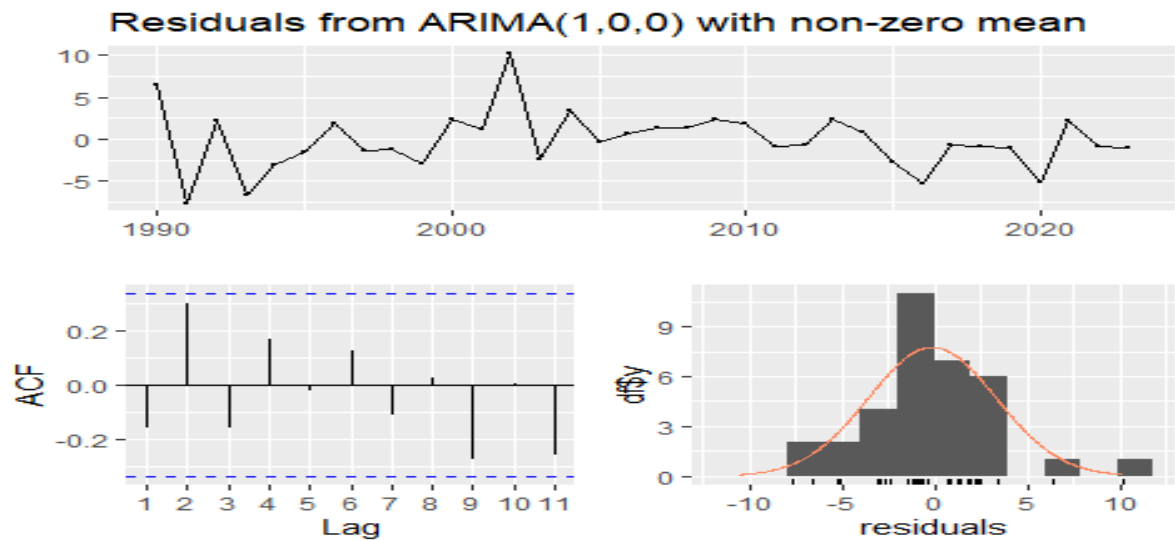


Figure f: Residuals from ARIMA (1,0,0) with non-zero mean
Source: Author's analysis, 2025

Before concluding that our ARIMA (1,0,0) specification has fully accounted for serial dependence, we apply the Ljung–Box test to the residuals. Table 6 reports the Q-statistic, degrees of freedom, and p-value for lags up to seven. A non-significant result ($p = 0.25$) confirms we cannot reject the null hypothesis of white-noise residuals, indicating no remaining autocorrelation and validating the model's adequacy. The differences between what the model predicts and what actually happened look like pure noise, with no hidden ups and downs that the model missed. That's precisely what you want when your model has done a good job.

Table 6. Ljung–Box Test on Model Residuals

Test Statistic (Q^*)	Degrees of Freedom	p-Value	Decision
7.8831	6	0.2468	Accept H_0

Null hypothesis (H_0): Residuals are uncorrelated (white noise).

4.9 Forecasts model accuracy

This section assesses the predictive validity of our ARIMA (1,0,0) model by computing a comprehensive set of one-step-ahead error metrics on the training data. To determine the reliability of GDP forecasts under different growth scenarios. Table 6 is a concise summary of the training-set error metrics and what each tells us about the one-step-ahead GDP forecasts:

Table 6: Training-Set Error Measures

Metric	Value	What It Means
Mean Error (ME)	-0.13	On average, forecasts overshoot actual GDP by 0.13 index points (slight upward bias).
Root Mean Square Error	3.40	Typical forecast is off by about 3.4 index points; large misses count more heavily.
Mean Absolute Error (MAE)	2.54	Average absolute miss is 2.5 index points-roughly the "usual" forecast gap.
Mean Percentage Error	16.50%	Forecasts run about 16½% % too high on average (percentage bias).
Mean Absolute % Error	199.49%	Absolute miss averages nearly twice the actual values-this is inflated by small-value quarters.
Mean Absolute Scaled Error	0.93	Model is ~7% more accurate than simply "guessing no change" (benchmark MASE = 1.00).
Residual ACF (1)	-0.16	Little to no one-quarter "memory" remains in the errors, and the residuals look randomised.

The one-step-ahead forecasts exhibit minimal bias, with a mean error of -0.13 index points indicating a slight tendency to overshoot. Dispersion metrics show that typical forecast deviations range from 2.5 points (MAE) to 3.4 points (RMSE), while a MASE of 0.93 confirms a 7% improvement over a naive "no-change" rule. Low base values inflate percentage-based errors and therefore offer limited practical insight.

Residual autocorrelation at lag 1 ($ACF_1 = -0.16$) is effectively zero, demonstrating that no systematic patterns remain in the errors. In operational terms, planners should assume a forecast uncertainty of ± 3 index points when setting annual revenue and expenditure targets. With no lingering bias or serial dependence, these ARIMA-based projections can serve as a trusted baseline, provided that contingency buffers are maintained to absorb inevitable deviations.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study set out to develop, validate, and deploy a univariate ARIMA framework for forecasting Nigeria's real GDP, gauge its performance under alternative growth scenarios, and translate the resulting projections into actionable policy tools. Applying the classic Box–Jenkins methodology to annual GDP data (1990–2023), we confirmed non-stationarity in levels, achieved stationarity via first differencing, and identified an ARIMA (1,0,0) model with drift as the most parsimonious yet effective specification. Diagnostic checks, including ACF/PACF analysis, Augmented Dickey–Fuller tests, Ljung–Box statistics, and residual normality assessments, validate that the model captures all serial dependence and leaves only white-noise errors. In-sample accuracy metrics (RMSE = 3.40, MAE = 2.54, MASE = 0.93) demonstrate the model's clear superiority over a naive "no-change" rule, with one-year forecast errors of $\pm 2\frac{1}{2}$ – $3\frac{1}{2}$ index points. Ten-period projections converge gradually toward the long-run mean, while 95% confidence intervals widen

over time, highlighting persistent uncertainty. Scenario adjustments to the drift term further illustrate downside and upside growth paths, offering a transparent toolkit for policymakers. These findings complement richer multivariate studies (Ayadi et al., 2000; Alhassan & Kilishi, 2016) by providing a streamlined, easily updated univariate forecast of aggregate output. The ARIMA-based projections thus fill a critical gap in Nigeria's policy arsenal, providing precise point forecasts, quantified error bands, and scenario-adjusted paths, all of which are essential for fiscal and reserve management in a commodity-driven environment.

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