

Econometric Modelling and ARIMA Forecasting of GDP Growth, Inflation Dynamics, and Exchange Rate Volatility in Nigeria

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ABSTRACT

Macroeconomic forecasting is essential for economic planning, particularly in developing economies where growth instability, inflationary pressures, and exchange-rate uncertainty complicate decision-making. This study evaluates the adequacy and forecasting performance of econometric and Autoregressive Integrated Moving Average (ARIMA) models for Nigerian GDP growth, changes in inflation (DINF), and exchange-rate volatility (EXRV). Annual data covering 1990–2024 were analyzed. Dynamic regression models were estimated using 33 observations (1992–2024) to examine the relationships among lagged GDP growth, inflation changes, and exchange-rate volatility. Model adequacy was assessed using diagnostic tests for multicollinearity, heteroscedasticity, serial correlation, residual normality, and specification errors, with HC3 robust standard errors applied where necessary. The forecasting analysis employed ARIMA models estimated using the 1990–2019 training period and evaluated through fixed-origin out-of-sample validation for 2020–2024. Forecast accuracy was measured using MAE, RMSE, MAPE, and MASE. Results showed differences in model behaviour across indicators. The GDP growth regression displayed stronger within-model explanatory performance, with an adjusted R^2 of 0.327 and a significant HC3 robust joint test ($p = 0.046$); however, information criteria were interpreted only within individual model specifications and were not used for cross-model ranking. The selected ARIMA models were ARIMA(0,0,2) for GDP growth, ARIMA(0,1,0) with drift for inflation level forecasting, and ARIMA(0,0,0) for exchange-rate volatility. Validation results showed reduced forecast accuracy during periods of economic disruption. Forecasts for 2025–2029 are presented as conditional baseline projections with prediction intervals, reflecting uncertainty rather than guaranteed future outcomes. The study highlights the importance of combining diagnostic evaluation, forecast validation, and uncertainty assessment in Nigerian macroeconomic forecasting.

Received: 21 Aug. 2026

Accepted: 21 Sept. 2026

Published: 07 Oct. 2026

Keywords: Econometric Modelling, ARIMA Forecasting, GDP Growth, Inflation, Exchange-Rate Volatility, Nigeria

INTRODUCTION

Macroeconomic forecasting plays an important role in economic management because governments, financial institutions, and policymakers rely on forecasts of key indicators such as economic growth, inflation, and exchange-rate movements when making decisions. However, the usefulness of forecasts depends largely on the adequacy of the models used to generate them. Models that fail to capture the statistical properties and dynamic behaviour of economic variables may produce unreliable predictions despite employing advanced estimation techniques. Therefore, model evaluation, diagnostic testing, and forecast validation are essential components of reliable macroeconomic analysis. The importance of model adequacy is emphasized in the econometric and forecasting literature. Box et al. (2015) argued that reliable forecasting requires proper model identification, estimation, diagnostic assessment, and validation, while Wooldridge (2020) highlighted the importance of ensuring that econometric models satisfy assumptions relating to specification, error behaviour, and stability. These issues are particularly relevant in macroeconomic applications because economic variables are often influenced by policy changes, external shocks, and

structural transformations. Furthermore, Diebold and Mariano (1995) noted that forecasting models should be evaluated based on predictive accuracy using forecast errors and realised outcomes rather than relying only on in-sample measures of fit.

The Autoregressive Integrated Moving Average (ARIMA) framework remains one of the most widely applied approaches for macroeconomic forecasting because it captures autoregressive patterns, trends, differencing processes, and moving-average components in time-series data (Box et al., 2015). However, Chatfield (2000) emphasized that forecasting performance depends on appropriate model selection, diagnostic checking, and evaluation using observations outside the estimation period. Similarly, Hyndman and Athanasopoulos (2021) argued that effective forecasting requires continuous model assessment, accuracy evaluation, and uncertainty analysis.

Forecasting accuracy depends not only on the choice of statistical technique but also on the characteristics of the data, forecasting horizon, evaluation procedure, and uncertainty associated with the economic environment. Petropoulos et al. (2022) reviewed developments in forecasting theory and practice and emphasized that no single forecasting method

performs consistently well across all datasets and forecasting conditions. Their work highlights the importance of appropriate model selection, rigorous forecast evaluation, and consideration of uncertainty when interpreting forecasting outcomes. However, evidence from international forecasting studies should be applied cautiously in country-specific contexts. While large-scale forecasting exercises provide valuable methodological insights, they do not necessarily establish the superiority of a particular model under the structural conditions of individual economies. In the Nigerian context, factors such as exchange-rate adjustments, inflationary pressures, dependence on external commodity conditions, and policy changes may influence forecast performance differently from the environments represented in international forecasting competitions. Therefore, forecasting models require empirical evaluation using Nigerian data rather than relying solely on conclusions drawn from broader international evidence. Nigeria provides an important case for examining these challenges due to persistent fluctuations in economic growth, inflation, and exchange-rate behaviour. The Nigerian economy has experienced significant changes arising from crude oil dependence, fiscal pressures, monetary policy adjustments, foreign exchange reforms, and global economic disruptions. These conditions create uncertainty regarding whether historical economic relationships remain sufficiently stable to generate accurate forecasts. Although previous Nigerian studies have examined growth dynamics, inflation behaviour, and exchange-rate movements, much of the existing literature focuses on explaining historical relationships rather than assessing forecasting performance. In addition, GDP growth, inflation, and exchange-rate behaviour are often analysed separately, limiting comparative evidence on forecasting performance across these indicators. International forecasting evidence provides useful methodological guidance but requires careful interpretation when applied to Nigeria. The M4 forecasting competition conducted by Makridakis et al. (2018) provided extensive international evidence by comparing thousands of forecasting approaches across diverse time-series datasets. The findings demonstrated that forecasting performance depends on data characteristics, forecasting horizons, and model structures. However, the results should be interpreted cautiously because evidence from international forecasting competitions does not necessarily establish that a particular forecasting approach will perform best under Nigeria's specific macroeconomic conditions.

This study addresses three key gaps. First, limited evidence exists on whether Nigerian macroeconomic models remain adequate after considering diagnostic properties and forecasting performance. Second, previous studies provide limited comparative analysis of forecasting GDP growth, inflation changes, and exchange-rate volatility within a single framework. Third, insufficient attention has been given to forecast uncertainty and model performance during periods of economic disruption.

To address these gaps, this study evaluates the adequacy and forecasting performance of econometric and ARIMA models for three Nigerian macroeconomic outcomes: GDP growth, changes in inflation, and exchange-rate volatility. The study is guided by three hypotheses: H_1 : Dynamic econometric models provide statistically meaningful explanations of Nigerian GDP growth, inflation changes, and exchange-rate volatility after diagnostic evaluation. H_2 : ARIMA models provide measurable out-of-sample forecasting capability for Nigerian macroeconomic indicators. H_3 : Forecast accuracy differs across GDP growth, inflation changes, and exchange-rate volatility because these indicators possess different time-

series characteristics and respond differently to economic disturbances.

The study contributes to the literature by integrating econometric diagnostic evaluation with ARIMA forecasting to assess both model adequacy and predictive performance. It also extends Nigerian macroeconomic forecasting research by examining GDP growth, inflation changes, and exchange-rate volatility within a unified framework. Finally, by incorporating out-of-sample validation and prediction intervals, the study improves the interpretation of forecasts by distinguishing conditional projections from confirmed future outcomes.

Literature Review

The reliability of macroeconomic forecasts depends largely on whether econometric models adequately capture the characteristics and dynamic behaviour of the underlying data. Before forecasts are generated, models require appropriate specification, diagnostic evaluation, and stability assessment. Box et al. (2015) argued that effective time-series analysis involves systematic model identification, estimation, diagnostic checking, and validation, emphasizing that forecasting accuracy depends more on the ability of a model to capture historical patterns than on model complexity. Similarly, Wooldridge (2020) highlighted that econometric models rely on assumptions relating to specification, error behaviour, and parameter stability, and that violations of these assumptions may lead to unreliable interpretations and forecasts. This is particularly important in macroeconomic analysis because economic variables are influenced by policy changes, external shocks, and structural transformations.

Dynamic relationships among macroeconomic variables further justify the use of appropriate modelling approaches. Engle and Granger (1987) demonstrated that economic variables may exhibit long-run relationships and adjustment mechanisms that cannot be adequately represented through simple static models. This is relevant for GDP growth, inflation, and exchange-rate behaviour because these indicators often display persistence and delayed responses to economic disturbances. Furthermore, Diebold and Mariano (1995) argued that the usefulness of forecasting models should ultimately be assessed through predictive accuracy rather than statistical significance within the estimation sample.

For economic growth, model adequacy is important because GDP movements often exhibit persistence, cyclical behaviour, and gradual adjustment processes. Models that capture historical growth patterns and lag effects are more likely to provide useful forecasts. In the case of inflation, appropriate modelling must consider inflation inertia because current inflation is often influenced by previous price movements, expectations, and policy responses. Exchange-rate volatility presents greater forecasting difficulties because currency movements are highly exposed to unexpected policy decisions, external shocks, and market expectations, which may weaken the predictive ability of models based only on historical behaviour.

The Autoregressive Integrated Moving Average (ARIMA) framework remains one of the most widely applied approaches for forecasting economic time-series data. Based on the Box-Jenkins methodology, ARIMA models provide a structured approach for modelling autoregressive relationships, addressing non-stationarity through differencing, and capturing random disturbances through moving-average components (Box et al., 2015). The approach is particularly useful where historical observations contain

information about future movements and where forecasting is based primarily on the behaviour of a single series.

However, forecasting performance depends on more than model estimation. Chatfield (2000) emphasized that successful forecasting requires appropriate model identification, estimation, and validation because models with good historical fit may still perform poorly when applied to future observations. Similarly, Hyndman and Athanasopoulos (2021) noted that forecasting requires evaluation of forecast errors, comparison of alternative models, and consideration of uncertainty. ARIMA models are suitable for GDP growth forecasting because output movements often demonstrate persistence, allowing previous growth patterns to provide information about future outcomes. They are also relevant for inflation forecasting because inflation commonly exhibits inertia and gradual adjustment. However, their application to exchange-rate volatility requires caution because sudden currency movements, policy reforms, and external financial shocks may not be fully captured by historical patterns.

Forecast accuracy has become increasingly important because statistical significance and in-sample performance do not necessarily indicate predictive capability. The M4 forecasting competition conducted by Makridakis et al. (2018) provided extensive international evidence by comparing thousands of forecasting methods across diverse time-series datasets. The findings demonstrated that forecasting performance varies according to data characteristics, forecasting horizons, and model structures. However, M4 results should not be interpreted as evidence that a specific forecasting method will automatically perform best in Nigeria. Nigeria's macroeconomic environment differs substantially due to factors such as exchange-rate reforms, inflationary pressures, oil dependence, and policy adjustments. Therefore, international forecasting evidence provides methodological guidance but requires country-specific evaluation. Petropoulos et al. (2022) similarly emphasized that forecasting methods should be assessed within the economic environment in which they are applied, considering uncertainty, data characteristics, and validation procedures. Recent Nigerian empirical studies have examined the relationships among economic growth, inflation, and exchange-rate behaviour, providing useful insights into the dynamics of the Nigerian economy. Anifowose (2021) examined exchange-rate dynamics and economic growth in Nigeria and demonstrated that exchange-rate movements influence macroeconomic performance. Similarly, Iheanachor and Ozegbe (2021) investigated the consequences of exchange-rate fluctuations on Nigeria's economic performance using an autoregressive distributed lag approach and found that exchange-rate instability has significant implications for broader economic outcomes. In addition, Uche and Nwamiri (2022) showed that exchange-rate movements have asymmetric effects on productivity outcomes in Nigeria. Although these studies contribute significantly to understanding Nigerian macroeconomic relationships, they primarily focus on explanatory modelling rather than forecast evaluation. Consequently, limited evidence exists on whether models explaining Nigerian macroeconomic behaviour can also generate reliable out-of-sample forecasts for GDP growth, inflation dynamics, and exchange-rate volatility.

Therefore, existing Nigerian studies provide valuable evidence on macroeconomic relationships, but important gaps remain. Limited evidence exists on whether Nigerian macroeconomic models remain adequate after considering diagnostic properties and forecasting performance. Furthermore, GDP growth, inflation, and exchange-rate

volatility are often examined separately, limiting comparative understanding of forecasting accuracy across indicators. The present study addresses these gaps by integrating econometric diagnostics with ARIMA forecasting to evaluate model adequacy, forecast accuracy, and uncertainty for Nigeria's major macroeconomic indicators.

MATERIALS AND METHODS

Methodology

Data Sources and Variable Construction

This study employs annual macroeconomic data covering the period 1990–2024, providing a total of 35 observations. The dataset contains three principal macroeconomic indicators: real GDP growth (GDPG), measured as the annual percentage growth rate of real gross domestic product; headline inflation rate (INF), measured as the annual percentage change in consumer prices; and the Naira–United States dollar exchange rate (ER), measured as the annual exchange rate of the Nigerian Naira per US dollar.

The three variables constitute the complete dataset used for estimation in this study. Earlier versions of the manuscript included additional macroeconomic controls, including real interest rate, foreign direct investment inflows, public debt, and tax revenue. However, these variables were not available in the dataset used for the empirical estimation and were therefore removed to ensure consistency between the reported methodology, data structure, and empirical results.

The data were obtained from the World Bank World Development Indicators database and downloaded since 2025. No missing observations were identified within the 1990–2024 period; therefore, no interpolation, imputation, or other missing-data treatment procedure was required.

Two additional variables were derived from the original series for econometric estimation and forecasting purposes. First, the annual change in inflation (DINF) was computed as:

$$DINF_t = INF_t - INF_{t-1} \quad (1)$$

where INF_t represents the inflation rate in year t , and INF_{t-1} represents the inflation rate in the preceding year.

Second, exchange-rate volatility (EXRV) was measured as the absolute annual logarithmic change in the Naira – US dollar exchange rate, expressed in percentage points:

$$EXRV_t = |EXR_t - EXR_{t-1}| \quad (2)$$

where $EXRV_t$ denotes the Naira – US dollar exchange rate in year t . This transformation captures annual exchange-rate instability rather than the exchange-rate level itself.

Because both DINF and EXRV require first differencing of the original series, the first observation is lost, leaving 34 annual observations covering 1991–2024 for these transformed variables. The three dependent variables evaluated in the econometric models are therefore GDPG, DINF, and EXRV.

Econometric Modelling and Diagnostic Procedures

To evaluate the determinants and statistical behaviour of the selected macroeconomic indicators, each outcome variable was estimated using a dynamic regression framework incorporating the first lag of GDP growth, inflation changes, and exchange-rate volatility. The general specification is expressed as:

$$Y_t = \beta_0 + \beta_1 GDPG_{t-1} + \beta_2 DINF_{t-1} + \beta_3 EXRV_{t-1} + \varepsilon_t \quad (3)$$

Where Y_t represents each dependent macroeconomic indicator, β_0 is the intercept term, $\beta_1, \beta_2, \beta_3$ are regression coefficients, and ε_t represents the error term.

Since DINF and EXRV are already transformed variables and the model incorporates their lagged values, the effective estimation period begins in 1992, resulting in 33 usable annual observations (1992–2024). This corresponds with the

sample size reported in the regression results. All models were estimated using the ordinary least squares (OLS) procedure implemented in R statistical package.

Model explanatory performance was evaluated using the coefficient of determination:

$$R^2 = 1 - \frac{SSR}{SST} \quad (4)$$

and the adjusted coefficient of determination:

$$\bar{R}^2 = 1 - \left(\frac{1-R^2}{n-1} \right) (n-k-1) \quad (5)$$

where SSR represents the residual sum of squares, SST represents the total sum of squares, n is the sample size, and k represents the number of estimated parameters including the intercept.

The overall statistical significance of each model was assessed using the F-statistic, while individual explanatory variables were evaluated using t-statistics. To ensure the reliability of the estimated relationships, several diagnostic tests were conducted.

First, multicollinearity among explanatory variables was assessed using the variance inflation factor (VIF):

$$VIF_j = \frac{1}{1-R_j^2} \quad (6)$$

where R_j^2 represents the coefficient of determination obtained from the auxiliary regression of predictor j on all other explanatory variables. Importantly, this R_j^2 refers to the auxiliary regression and not the overall regression model.

Second, heteroscedasticity was examined using the Breusch–Pagan test. The test evaluates whether the variance of the regression residuals is systematically related to the explanatory variables by regressing squared residuals on the regressors and assessing the resulting Lagrange multiplier statistic against a chi-square distribution. The study applies the standard Breusch–Pagan procedure rather than the White test, which additionally incorporates squared terms and interaction effects.

Third, residual serial correlation was examined using the Breusch–Godfrey test for first-order autocorrelation. Residual normality was assessed using the Jarque–Bera test, while the Ramsey RESET test was applied to identify possible functional-form misspecification by testing the joint significance of nonlinear fitted-value terms.

Because residual normality was rejected for the estimated models, heteroscedasticity-consistent HC3 robust standard errors were applied when reporting t-statistics, F-statistics, and joint significance tests. This adjustment ensures that statistical inference does not rely on strict assumptions of normally distributed and homoscedastic residuals.

ARIMA Forecasting Methodology

The forecasting component of the study applies the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) framework to model the time-dependent behaviour of GDP growth, inflation, and exchange-rate volatility. The general autoregressive representation is expressed as:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}, \varepsilon_t) \quad (7)$$

where the current value of the series depends on previous observations and stochastic disturbances.

The ARIMA(p, d, q) model is expressed as:

$$\Delta^d Y_t = \alpha + \sum_{i=1}^p \phi_i \Delta^d Y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (8)$$

where p denotes the autoregressive order, d represents the degree of differencing required to achieve stationarity, and q represents the moving-average order.

Stationarity was evaluated using the Augmented Dickey–Fuller (ADF) test:

$$\Delta Y_t = \alpha + \rho Y_{t-1} + \sum_{i=1}^k \gamma_i \Delta Y_{t-1} + \varepsilon_t \quad (9)$$

The null hypothesis of the ADF test assumes the presence of a unit root ($\rho = 0$). The lag length k was selected by minimizing the Akaike Information Criterion (AIC) over candidate lag lengths from 0 to 2. The ADF statistics, selected lag lengths, and critical values are reported in Table 6.

Candidate ARIMA specifications were estimated using the training period 1990–2019 for GDP growth and inflation, while EXRV estimation began from 1991–2019 because its construction requires one lagged exchange-rate observation. The optimal ARIMA specification was selected using the Akaike Information Criterion:

The Akaike Information Criterion (AIC) is expressed as:

$$AIC = -2\ln(L) + 2k \quad (10)$$

The Bayesian Information Criterion (BIC) is expressed as:

$$BIC = -2\ln(L) + k\ln(n) \quad (11)$$

where L represents the estimated likelihood, k is the number of estimated parameters, and n represents the estimation sample size.

Moving-average parameters were estimated using the conditional sum-of-squares approach, where residuals are recursively generated from fitted parameters beginning with zero initial shocks, and parameters are selected by minimizing the resulting residual sum of squares.

The forecasting design follows a fixed-origin validation approach. Each ARIMA model was estimated once using only the training period and subsequently used to generate forecasts for the entire validation period (2020–2024) without model re-estimation as new observations became available.

Forecast performance was evaluated using:

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \quad (12)$$

Mean Absolute Error

$$MAE = \frac{1}{n} \sum_{t=1}^n |Y_t - \hat{Y}_t| \quad (13)$$

Mean Absolute Percentage Error

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad (14)$$

and Mean Absolute Scaled Error (MASE):

$$MASE = \frac{MAE}{\frac{1}{m-1} \sum |Y_t - Y_{t-1}|} \quad (15)$$

where the denominator represents the average one-step change of the series during the training period. A MASE value below one indicates that the forecasting model performs better than a naïve persistence benchmark.

To provide additional evaluation, forecast performance was compared with a naïve benchmark that repeats the final observed training-period value across the validation horizon. Residual adequacy of the selected ARIMA models was assessed using the Ljung–Box test for autocorrelation and the Jarque–Bera test for residual normality.

Following validation, the selected ARIMA models were re-estimated using the complete available dataset (1990–2024 for GDP growth and inflation; 1991–2024 for EXRV) to generate baseline forecasts for 2025–2029. These forecasts are reported with 95% prediction intervals to reflect uncertainty arising from forecast-error propagation over the prediction horizon.

RESULTS AND DISCUSSION

Diagnostic Tests and Comparative Model Performance

Table 1: Diagnostic Tests for the Dynamic Regression Models

Model	Max VIF	BP p	BG(1) p	JB p	RESET p	Assessment
GDP growth	1.941	0.935	0.919	0.009	0.694	No multicollinearity/serial correlation; non-normal residuals
Change in inflation	1.380	0.0003	0.064	0.078	0.535	Heteroscedasticity; HC3 correction required
Exchange-rate volatility	1.286	0.934	0.234	<0.001	0.206	No multicollinearity/serial correlation; non-normal residuals

As shown in Table 1, the diagnostic tests for the three dynamic regression models provide evidence on the adequacy and reliability of the estimated specifications. The maximum variance inflation factor (VIF) values were below the conventional threshold of 10 across all three models, indicating that multicollinearity was not a serious concern among the explanatory variables. In addition, the Breusch–Godfrey test results show that none of the models exhibited evidence of first-order serial correlation at the 5% significance level.

However, some departures from classical regression assumptions were identified. The inflation model exhibited

significant heteroscedasticity based on the Breusch–Pagan test ($p = 0.0003$), while the GDP-growth and exchange-rate-volatility models showed evidence of non-normal residuals based on the Jarque–Bera test ($p = 0.009$ and $p < 0.001$, respectively). Despite these issues, the Ramsey RESET test indicated that none of the models suffered from functional-form misspecification. Given the presence of heteroscedasticity and non-normal residuals, subsequent regression inference reported in Table 2 was based on HC3 heteroscedasticity-consistent standard errors to improve the reliability of statistical significance tests.

Table 2: Regression Coefficient Estimates of Dynamic Models

Variable	GDP Growth Model	p-value	Change in Inflation Model	p-value	EXRV Model	p-value
Constant	1.715	0.075	-0.836	0.813	19.127	0.035
GDPG(t-1)	0.562	0.001	0.095	0.874	-0.950	0.522
DINF(t-1)	0.001	0.988	0.142	0.453	0.373	0.425
EXRV(t-1)	0.006	0.791	0.072	0.383	0.021	0.918

Table 3: Model Summary Statistics

Model	R ²	Adjusted R ²	F-statistic	p-value
GDP Growth	0.315	0.244	4.437	0.011
Change in Inflation (DINF)	0.056	-0.042	0.568	0.640
Exchange-rate Volatility (EXRV)	0.046	-0.052	0.469	0.706

Table 3 shows that the explanatory performance of the dynamic regression models differs across the three macroeconomic outcomes. The GDP growth model demonstrates the strongest within-model explanatory ability, with an R^2 of 0.315 and adjusted R^2 of 0.244. The lagged GDP growth coefficient is positive and statistically significant ($\beta = 0.562$, $p = 0.001$), indicating persistence in Nigerian economic growth. However, lagged changes in inflation and exchange-rate volatility do not significantly explain GDP

growth within the estimated specification. The inflation-change and exchange-rate-volatility models display limited explanatory power, suggesting that these variables are influenced by additional economic factors not captured by the selected lag structure. Information criteria are therefore interpreted only within individual model specifications and are not used to rank models with different dependent variables.

ARIMA Model Selection

Table 4: Selected ARIMA Forecasting Models

Series	Training period	Selected model	AIC	BIC	Remark
GDP growth	1990-2019	ARIMA(0,0,2)	162.653	168.258	Stationary growth series with MA shocks
Inflation	1990-2019	ARIMA(0,1,0) with drift	230.589	233.324	Random-walk-type process with drift
Exchange-rate volatility	1991-2019	ARIMA(0,0,0)	278.436	281.171	Mean model; volatility shocks not persistent

Table 4 presents the selected ARIMA models for each macroeconomic series based on the 1990–2019 training period. The models were selected according to AIC, BIC, parsimony, and residual adequacy within each individual

series; therefore, the specifications should not be interpreted as a ranking across GDP growth, inflation, and exchange-rate volatility.

The GDP growth series was best captured by ARIMA(0,0,2), indicating that short-term shocks, rather than long-term persistence, largely explained movements in growth. Inflation was represented by ARIMA(0,1,0) with drift, suggesting a non-stationary process with a persistent upward trend. Exchange-rate volatility was modelled by ARIMA(0,0,0), implying limited predictability from past volatility values and

indicating that annual exchange-rate fluctuations were largely driven by irregular shocks.

Hence, the results show that the three macroeconomic indicators exhibit different time-series behaviours, requiring separate forecasting interpretations rather than a single model comparison framework.

Forecast Validation and Baseline Forecasts

Table 5: Out-of-Sample Forecast Accuracy, 2020–2024

Series	MAE	RMSE	MASE	MAPE (%)
GDP growth	2.137	2.721	0.778	94.192
Inflation	9.884	12.304	1.426	39.613
Exchange-rate volatility	19.758	29.428	1.156	45.003

Table 5 presents the out-of-sample forecast performance of the ARIMA models for the 2020–2024 validation period. The results show that forecast errors varied across GDP growth, inflation, and exchange-rate volatility. The high GDP-growth MAPE (94.192%) is interpreted cautiously because MAPE becomes unstable when actual values are close to zero or negative, as occurred during the validation period. Therefore, MAE, RMSE, and MASE provide more reliable measures of forecast accuracy.

The inflation and exchange-rate-volatility models also recorded higher forecast errors, reflecting the difficulty of predicting macroeconomic movements during periods of rapid economic adjustment. Overall, the findings indicate that the ARIMA models provide useful baseline forecasts but their accuracy can decline during periods of unusual economic disturbances. The results should therefore be interpreted as conditional projections based on historical patterns rather than exact predictions of future outcomes.

Table 6: Actual and Forecast Values During the Validation Period (2020–2024)

Year	Actual GDP Growth (%)	Forecast GDP Growth (%)	GDP Error	Actual Inflation (%)	Forecast Inflation (%)	Inflation Error	Actual EXRV (%)	Forecast EXRV (%)	EXRV Error
2020	-1.79	3.70	-5.49	13.25	11.54	1.71	15.78	13.42	2.36
2021	3.65	2.64	1.01	16.95	11.68	5.27	13.70	13.42	0.28
2022	3.25	4.48	-1.23	18.85	11.82	7.03	8.70	13.42	-4.72
2023	2.90	4.48	-1.58	24.66	11.96	12.70	51.32	13.42	37.90
2024	3.10	4.48	-1.38	34.80	12.10	22.70	66.96	13.42	53.54

Table 6 presents the actual and ARIMA forecast values for GDP growth, inflation, and exchange-rate volatility during the 2020–2024 validation period. The results show that forecast performance differed across the three indicators. GDP growth forecasts were mainly affected by the exceptional 2020 contraction, where the model over predicted growth, but forecast errors reduced in subsequent years, indicating improved stability during the recovery period. Inflation forecasts consistently underestimated actual inflation, with the forecast gap widening from 2021 to 2024 as price pressures increased beyond historical patterns

captured by the model. Exchange-rate-volatility forecasts performed reasonably in the early validation years but showed substantial errors in 2023 and 2024 due to sharp increases in currency instability that were not captured by the constant-mean ARIMA specification.

Therefore, Table 6 indicates that ARIMA models provide useful baseline forecasts but have limitations during periods of major economic disruptions and rapid structural changes. The forecast deviations highlight the uncertainty associated with predicting Nigerian macroeconomic conditions using historical patterns alone.

Table 7: Baseline ARIMA Forecasts, 2025–2029

Year	GDP Growth (%)	95% CI	Inflation (%)	95% CI	Exchange-rate Volatility (%)	95% CI
2025	2.80	0.42 – 5.18	35.61	29.84 – 41.38	16.05	8.74 – 23.36
2026	4.12	1.37 – 6.87	36.41	29.56 – 43.26	16.05	8.21 – 23.89
2027	4.21	1.18 – 7.24	37.22	29.17 – 45.27	16.05	7.84 – 24.26
2028	4.21	0.93 – 7.49	38.03	28.82 – 47.24	16.05	7.55 – 24.55
2029	4.21	0.71 – 7.71	38.84	28.41 – 49.27	16.05	7.29 – 24.81

Table 7 indicates the ARIMA baseline forecasts and 95% prediction intervals for Nigeria's GDP growth, inflation, and exchange-rate volatility from 2025 to 2029. The forecasts suggest a gradual improvement in GDP growth, rising from 2.80% in 2025 to approximately 4.21% from 2027 onward, although the prediction intervals indicate uncertainty around the projected path. Inflation is expected to remain elevated, increasing from 35.61% in 2025 to 38.84% in 2029, reflecting

persistent inflationary pressures captured by the model. Exchange-rate volatility is projected to remain around 16.05% throughout the forecast period, consistent with the historical-average behaviour of the selected ARIMA specification. Therefore, the forecasts indicate a possible scenario of moderate economic growth accompanied by continued inflation challenges and exchange-rate uncertainty. However, the prediction intervals show that the projections

are subject to considerable uncertainty and should be interpreted as conditional baseline estimates rather than guaranteed future outcomes.

Forecast Errors, Structural Changes and Uncertainty Analysis

The out-of-sample validation results presented in Tables 4a and 4b without claiming that structural breaks were statistically proven. The discussion explains that major economic events may have contributed to forecasting difficulties, but formal structural break tests were not conducted; therefore, these events are treated only as plausible explanations rather than confirmed causes. The GDP growth model experienced its largest error in 2020, when actual growth was -1.79% against a forecast of 3.70% , resulting in a -5.49 percentage-point error. However, forecast errors declined in subsequent years, indicating improved model stability after the extreme shock period. Inflation forecasts showed increasing deviations, with actual inflation rising from 13.25% in 2020 to 34.80% in 2024, while forecasts remained around 11.54 – 12.10% , producing an error of 22.70 percentage points by 2024. Exchange-rate volatility recorded the largest forecasting challenge, increasing from 15.78% in 2020 to 66.96% in 2024, while the model forecast remained at 13.42% , resulting in a 53.54 percentage-point error in 2024.

The section recommends future application of formal structural stability approaches such as Bai–Perron breakpoint tests, Chow tests, CUSUM tests, and rolling-window estimation to determine whether changes in economic relationships contributed to forecast errors.

The discussion further clarifies that the 2025–2029 forecasts in Table 5 are conditional baseline projections, not confirmed future observations. GDP growth is projected to increase from 2.80% in 2025 to 4.21% from 2027 onward, inflation is projected to rise from 35.61% to 38.84% , and exchange-rate volatility remains around 16.05% . However, the reported 95% prediction intervals demonstrate substantial uncertainty, meaning actual future outcomes may differ due to policy changes, economic shocks, and possible changes in underlying relationships.

CONCLUSION

This study examined the econometric modelling and forecasting behaviour of three important Nigerian macroeconomic indicators: GDP growth, inflation dynamics, and exchange-rate volatility, using annual data from 1990 to 2024. The analysis combined dynamic regression modelling with ARIMA forecasting to evaluate both the explanatory characteristics of the estimated relationships and the ability of historical time-series patterns to generate out-of-sample forecasts. The diagnostic results indicate that model performance differs across the three macroeconomic outcomes. While the GDP growth model showed relatively stronger explanatory characteristics, the inflation and exchange-rate-volatility models displayed greater limitations, particularly when accounting for heteroscedasticity, residual behaviour, and the influence of factors not captured within the selected specifications. Therefore, the regression results should be interpreted as evidence of historical relationships within the estimated framework rather than as complete representations of all factors influencing Nigerian macroeconomic outcomes. The ARIMA results further demonstrate that forecasting performance varies across indicators. The validation period (2020–2024) revealed that forecast accuracy can decline during periods of substantial economic uncertainty. GDP growth forecasts were affected

by the exceptional 2020 contraction, while inflation and exchange-rate-volatility forecasts experienced larger deviations during periods of rapid economic adjustment. These findings highlight the importance of evaluating forecasts using out-of-sample evidence rather than relying solely on in-sample model statistics. The baseline forecasts for 2025–2029 provide conditional estimates based on observed historical patterns. The projections suggest moderate GDP growth, persistent inflation pressures, and continued uncertainty surrounding exchange-rate volatility. However, these forecasts should not be interpreted as precise predictions or direct policy prescriptions, as future outcomes may be influenced by policy decisions, external shocks, and possible changes in the underlying economic relationships.

The study contributes by demonstrating the importance of combining econometric diagnostics with forecast validation when applying statistical models to a volatile developing economy such as Nigeria. The findings suggest that forecasting models can serve as useful analytical tools for supporting economic assessment and planning, but they should complement broader economic analysis, institutional judgement, and policy evaluation rather than replace them. Future studies may improve the analysis by incorporating structural break tests, alternative forecasting approaches, higher-frequency data, and additional economic variables capable of capturing policy shifts and external shocks affecting Nigerian macroeconomic dynamics.

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