On Forecasting Nigeria's GDP: A Comparative Performance of Regression with ARIMA Errors and ARIMA Method

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ABSTRACT: *This paper examines the application of autoregressive integrated moving average (ARIMA) model and regression model with ARIMA errors for forecasting Nigeria's GDP. The data used in this study are collected from the official website of World Bank for the period 1990-2019. A response variable (GDP) and four predictor variables are used for the study. The ARIMA model is fitted only to the response variable, while regression with ARIMA errors is fitted on the data as a whole. The Akaike Information Criterion Corrected (AICc) was used to select the best model among the selected ARIMA models, while the best model for forecasting GDP is selected using measures of forecast accuracy. The result showed that regression with ARIMA(2,0,1) errors is the best model for forecasting Nigeria's GDP.*

Keywords: ARIMA, Regression with ARIMA errors, AICc, Measures of Forecast Accuracy, GDP, Nigeria.

INTRODUCTION

Many time series methods are based on the analysis of historical data under the assumption that the past patterns in the data can be used to forecast future events (Malgorzata et al, 2018). In recent years, some of the popular ways of time series modeling is autoregressive integrated moving average (ARIMA) modeling, and regression model with ARIMA errors. The aim of ARIMA model is to carefully study the past observations of a time series to develop an appropriate model which can predict future values for the series. However, ARIMA model is only applicable on one dependent (response) variable which is indexed with time. The problem with this is that there is no full information on the variable, thus, if the response (dependent) variable is directly influenced by predictor (independent) variable(s), more information on the response (dependent) variable will be explained by the predictor(s) variable(s), and in this end, the linear regression model can be applied. But if these variables are indexed with time (which means that the residuals or errors will have a time series structure), and linear regression model is applied, then this will violate the usual assumption of independent errors made, and in addition, the estimates of coefficients and their standard errors will be wrong especially if the time series structure of the errors is ignored. In this situation, regression model with ARIMA errors is used instead.

Gross Domestic Product (GDP) is the total monetary or market value of all the finished goods and services produced within a country's borders in a specific period of time (Bing et al, 2016). GDP increases when the total value of goods and services that domestic producers sell to foreigners exceeds the total value of foreign goods and services that domestic consumers buy. GDP is an important index used to measure the economy development and the people's income of a country.

So many researches have done on the application of ARIMA on forecasting GDP, for instance, Wabomba et al (2016) examined Kenyan GDP for the period of 1960-2012 using ARIMA approach. The findings of their study showed that ARIMA(2,2,2) is the best model to forecast Kenyan GDP. Abonazel and Abd-Elftah (2019) studied the Egyptian GDP for the period 1965-2016, using ARIMA approach, and they carried out a forecast using the ARIMA(1,2,1) as the best model. Maity & Chatterjee (2012) studied and modeled the India's GDP from 1959 to 2011 using ARIMA and the selected model and forecasted for future GDP. With the aid of data from 1980 to 2013, Dritsaki (2015) modeled and forecasted Greece's real GDP using ARIMA. Uwimana et al (2018) modeled the GDP of 20 African countries using data from 1990 to 2016. Noura (2020) forecasted the GDP per Capita for Egypt and Saudi Arabia using ARIMA models. Youssef et al (2021) forecasted the economic activity of the biggest Gulf Cooperation Council countries from 1980 from 2020, using ARIMA method.

Van den Bossche et al (2007) investigated the frequency and severity of road traffic accident in Belgium using a regression model with ARIMA errors. Rupesh et al (2020) modeled and forecasted the number of road catastrophes of Great Britain from 2005 to 2015, using regression model with ARIMA errors.

This paper is significant in the sense that it forecasts the GDP using two different linear models, which are compared using forecast accuracies for better forecast. Reflecting on works done by other researchers on the prediction of GDP, it seen that more ARIMA applications had been used for forecasting GDP, while no or less of Regression with ARIMA errors has been applied. So, this paper applies Regression with ARIMA errors in the forecast of GDP, in order to close the gap.

MATERIALS AND METHODS

This paper adopts five variables. A response variable, y (Gross Domestic Product, GDP), and four predictor variables Exchange Rate (EXHR), Interest Rate (INTR), Export (EXP) and Import (IMP). The data used in this paper are those collected from the official website of the World Bank for a period 1990-2019.

The paper applies the method of Regression, ARIMA, and Regression with ARIMA errors on the data series. ARIMA is modeled on the GDP using the methodology of Box-Jenkins, while Regression with ARIMA errors is modeled on the GDP and the four predictor variables using both the least square methods and Box-Jenkins methods.

Linear Regression Model

In general, the linear regression model is given as

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t \tag{1}$$

where y_t is a linear function of the k predictor variables $(x_{1,t}, \cdots, x_{k,t})$ or the predictor variable $x_{1,t}$ and ε_t is a white noise(usually assumed to be an uncorrelated error term), and $(\beta_0, \beta_1, \cdots, \beta_k)$ are the parameters.

Multiple Linear Regression Modeling

Using the multiple linear regression analysis to develop a model connecting the response and the predictor variables, we observe critically the assumptions about the appropriate model by testing for the significance of the relationship. When the assumptions are met, it implies that the probability distributions of ε_t and y_t are normally distributed, each with the same variance, and are independent. However, some of the assumptions of linear regression model are usually violated when applied to time series data.

The parameters $(\beta_0, \cdots, \beta_k)$ in the model in equation (1) are estimated by $(b_0, \cdots, b_k)$ respectively using the Least Squared Method. The estimated multiple linear regression model is defined as

$$\hat{y}_t = b_0 + b_1 x_{1,t} \cdots + b_k x_{k,t} \tag{2}$$

where $b_i = \left(X'X\right)^{-1} X'y = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{pmatrix}$, $X'X = \begin{pmatrix} n & \sum x_{1,t} & \sum x_{2,t} & \cdots & \sum x_{k,t} \\ \sum x_{1,t} & \sum x_{1,t}^2 & \sum x_{1,t}x_{2,t} & \cdots & \sum x_{1,t}x_{k,t} \\ \sum x_{2,t} & \sum x_{2,t}x_{1,t} & \sum x_{2,t}^2 & \cdots & \sum X_{2,t}x_{k,t} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \sum x_{k,t} & \sum x_{k,t}x_{1,t} & \sum x_{k,t}x_{2,t} & \cdots & \sum x_{k,t}^2 \end{pmatrix}$,

$$X'Y = \begin{pmatrix} \sum y_t \\ \sum X_{1,t} y_t \\ \sum X_{2,t} y_t \\ \vdots \\ \sum X_{k,t} y_t \end{pmatrix}$$ and n is the sample size

Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA modeling approach expresses a variable as a weighted average of its own past values. ARIMA is a combination of Autoregressive (AR), Integrated (I), and Moving Average (MA), but in most cases, it is just the combination of AR and MA. The ARIMA models are usually applied to stationary data series where the function of the mean, variance, and autocorrelation remains constant over time (Jama, 2020).

AR process is a stationary process which expresses a response variable y_t as the function of the response variable's past values. The pth order of AR process denoted as $AR(p)$ is defined as

$$\left.\begin{aligned} y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \\ if\ \delta = 0, \qquad y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \end{aligned}\right\} \tag{3}$$

where y_t is the stationary response variable at time t, $y_{t-1}, \cdots, y_{t-p}$ are response variables at time $t-1, \cdots, t-p$ respectively, $\varepsilon_t \sim WN(0, \sigma^2)$, $\delta = \mu\left(1 - \phi_1 - \cdots - \phi_p\right)$ and $\phi_1, \cdots, \phi_p$are the parameters of the model AR

Defining equation (4) using a backshift operator, we have

$$\left.\begin{aligned} \left(1 - \phi_1 B - \cdots - \phi_p B^p\right) y_t = \varepsilon_t \\ \phi(B) y_t = \varepsilon_t \end{aligned}\right\} \tag{4}$$

MA process is a stationary process which is expressed in terms of the random errors of its past values. The qth order of MA process denoted as $MA(q)$ is defined as

$$\left.\begin{aligned} y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \\ if\ \mu = 0, \qquad y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \end{aligned}\right\} \tag{5}$$

Defining equation (6) using a backshift operator, we have

$$\left.\begin{aligned} \mu + \left(1 - \theta_1 B - \cdots - \theta_q B^q\right) \varepsilon_t = y_t \\ \mu + \theta(B) \varepsilon_t = y_t \end{aligned}\right\} \tag{6}$$

where ε_t is white noise, $\theta_1, \cdots, \theta_q$ are the weights for the MA process

Autoregressive Moving Average (ARMA) is the combination of stationary AR process and stationary MA process. $ARMA(p, q)$ model is defined as

$$y_t = \delta + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad (7)$$

Defining equation (8) using a backshift operator, we have

$$\phi(B) y_t = \delta + \theta(B)\varepsilon_t \quad (8)$$

ARMA model cannot be applied in all circumstances. However, when the time series data are non-stationary, then, the data need to be differenced or transformed in order to attain stationarity. in this case, ARIMA model is applied on the stochastic process (or response variable). ARIMA model is denoted as $ARIMA(p, d, q)$ is defined as

$$y'_t = \delta + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad (9)$$

Applying the backshift operator, we have

$$\phi(B)(1 - B)^d y_t = \delta + \theta(B)\varepsilon_t \quad (10)$$

where $\varepsilon_t \sim WN(0, \sigma^2)$, y'_t is the d difference of the response variable (or stochastic process) differencing of response variable, y_t is obtained using the following

$$\nabla^d y_t = y'_t = (1 - B)^d y_t = \sum_{k=0}^{d} \binom{d}{k} (-1)^k y_{t-k} \quad (11)$$

ARIMA Model Fitting

In fitting ARIMA to the stochastic process, we follow the Box-Jenkin's method. Firstly, we plot the data and check for stationarity. If the data show no evidence of stationarity, then we difference the data using equation (11).

The second part is to identify the model: we do that by computing sample autocorrelation function (ACF) and partial autocorrelation function (PACF), then plot ACF and PACF. Then we visualize the plots to identify the model. The sample ACF can be computed using

$$r_k = \frac{\sum_{t=1}^{T-k} (y_t - \bar{y}_t)(y_{t+k} - \bar{y}_t)}{\sum_{t=1}^{T} (y_t - \bar{y}_t)^2} \quad (12)$$

And the sample PACF can be computed using

$$\rho_{k,k} = \begin{cases} r_1, & if\ k = 1 \\ \dfrac{r_k - \sum_{j=1}^{k-1} (\rho_{k-1,j} . r_{k-j})}{1 - \sum_{j=1}^{k-1} (\rho_{k-1,j} . r_j)}, & if\ k > 1 \end{cases} \quad (13)$$

But if we have more than one model, we then choose the parsimonious model with the least Akaike Information Criterion Corrected (AICc). The AICc is obtained as follows:

$$\left.\begin{aligned} AIC &= -2lnL + 2p \\ AICc &= AIC + \frac{2p(p+1)}{n-p-1} \end{aligned}\right\} \tag{14}$$

where L is the likelihood of the data, p is the number of fitted model parameters, AIC is the Akaike Information Criterion, and n is the sample size.

Finally, once the parsimonious model is selected, we check for the adequacy of the model. This is done by obtaining the time series plot, residual plot, and the histogram of the residuals of the selected model. Once the selected model is adequate, it is then used to forecast the future values.

Regression Model with ARIMA Errors

If the errors ε_t in equation (1) contain autocorrelation, then the linear regression model with ARIMA error is written as

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t \tag{15}$$

And if the response variable y_t and the predictor variables $\left(x_{1,t}, \cdots, x_{k,t}\right)$ in equation (15) are stationary, then η_t the error series will follow an ARMA model defined as

$$\left.\begin{aligned} &\eta_t = \delta + \phi_1\eta_{t-1} + \cdots + \phi_p\eta_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} \\ if\ \delta = 0, \quad &\eta_t = \phi_1\eta_{t-1} + \cdots + \phi_p\eta_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} \end{aligned}\right\} \tag{16}$$

Where η_t the error series and δ is the drift

Again, if the response variable y_t and the predictor variables $\left(x_{1,t}, \cdots, x_{k,t}\right)$ in equation (15) are not stationary, we difference to attain stationarity. Then η_t the error series will follow an ARIMA model, and the regression model with ARIMA errors is defined as

$$y'_t = \beta_0 + \beta_1 x'_{1,t} + \cdots + \beta_k x'_{k,t} + \eta'_t \tag{17}$$

where the η_t the error series is defined as

$$\left.\begin{aligned} &\eta'_t = \delta + \phi_1\eta'_{t-1} + \cdots + \phi_p\eta'_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} \\ if\ \delta = 0, \quad &\eta'_t = \phi_1\eta'_{t-1} + \cdots + \phi_p\eta'_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} \end{aligned}\right\} \tag{18}$$

Measures of Forecast Adequacy

Once models are selected using the different statistical techniques, the measures of forecast accuracies are applied to select the best of them. This study adopts four measures of forecast accuracies, which are: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean

Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE) proposed by (Hyndman & Koehler, 2006).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{t=n}(y_t - \hat{y}_t)^2} \tag{19}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{t=n}|y_t - \hat{y}_t| \tag{20}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{t=n}100.\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{21}$$

$$\left.\begin{aligned} q_t &= \frac{|y_t - \hat{y}_t|}{\frac{1}{n-1}\sum_{t=2}^{t=n}|y_t - y_{t-1}|} \\ MASE &= \frac{1}{n}\sum_{t=1}^{t=n}|q_t| \end{aligned}\right\} \tag{22}$$

where n is the sample size, y_t is the response variable at time t, y_{t-1} is the response variable at time $t-1$, $\hat{y}_t$ is the forecast value, and q_t is scale error.

RESULTS/FINDINGS

Figure 1 shows the time plots for the GDP, and the predictor variables (Exchange Rate, Interest Rate, Export, and Import).

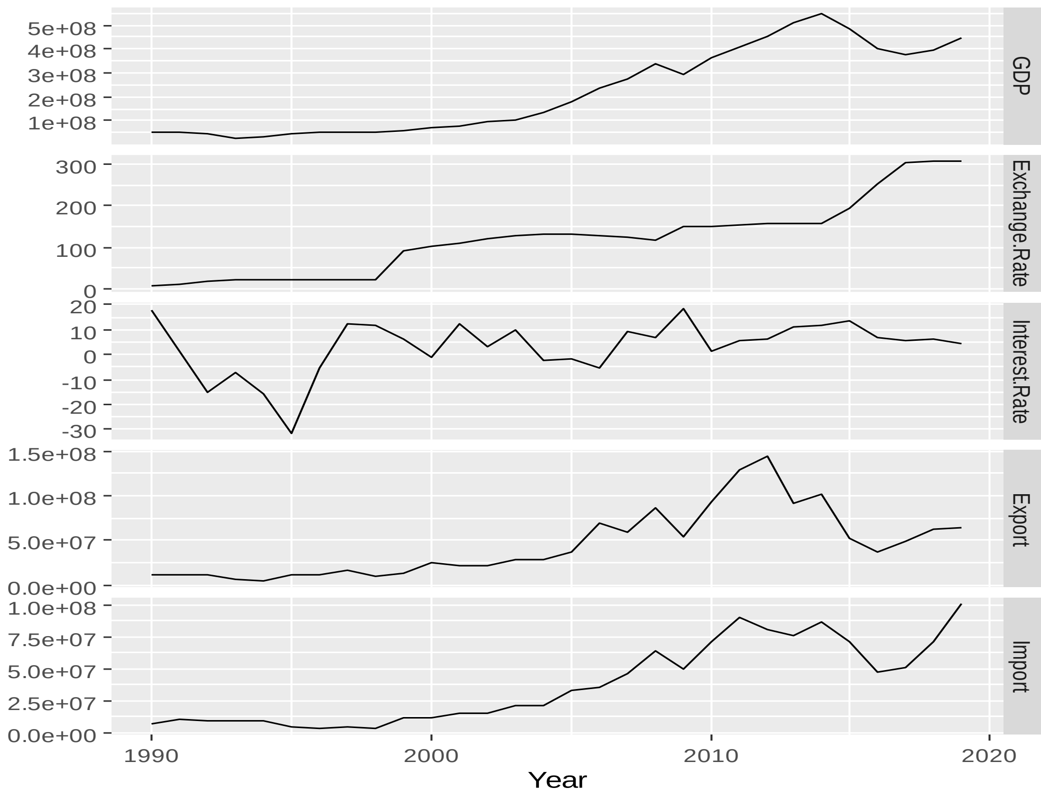

Figure 1. The plot of GDP, Exchange Rate, Interest Rate, Export and Import for the period 1990-2019

Table 1. Regression model with ARIMA errors selection

S/N	Models	AICc
1	ARIMA(0,0,0) with zero mean	1157.114
2	ARIMA(0,0,0) with non-zero mean	Inf.
3	ARIMA(0,0,1) with zero mean	1144.123
4	ARIMA(0,0,1) with non-zero mean	Inf.
5	ARIMA(1,0,0) with zero mean	Inf.
6	ARIMA(1,0,0) with non-zero mean	Inf.
7	ARIMA(2,0,0) with zero mean	Inf.
8	ARIMA(2,0,1) with zero mean	1112.803
9	ARIMA(2,0,1) with non-zero mean	Inf.

Regression with ARIMA(2,0,1) errors in Table 1 has the lowest Akaike Information Criterion Corrected (AICc) of 1112.803 among the rest of the models, and it is considered the best model for forecasting the Nigerian GDP. The estimated coefficients of fitted model (Regression with

ARIMA(2,0,1) errors) are given in Table 2. Figure shows the plots of regression errors and ARIMA errors.

Table 2. Estimated coefficients of regression model with ARIMA(2,0,1) errors

	ar1	ar2	ma1	EXHR	INTR	EXP	IMP
	1.4752	-0.4852	0.5854	-299314.6	-1137306.4	0.1977	1.6697
Standard Error (se)	0.2542	0.2545	0.4085	139652.3	320966.5	0.1208	0.3033

The estimated regression model with ARIMA(2,0,1) errors is given as

$$\left.\begin{aligned} GDP = -299314.6(EXHR)_t - 1137306(INTR)_t + 0.1977(EXP)_t + 1.6697(IMP)_t + \eta_t \\ \eta_t = 1.4752\eta_{t-1} - 0.4852\eta_{t-2} + \varepsilon_t + 0.5854\varepsilon_{t-1} \end{aligned}\right\} \quad (10)$$

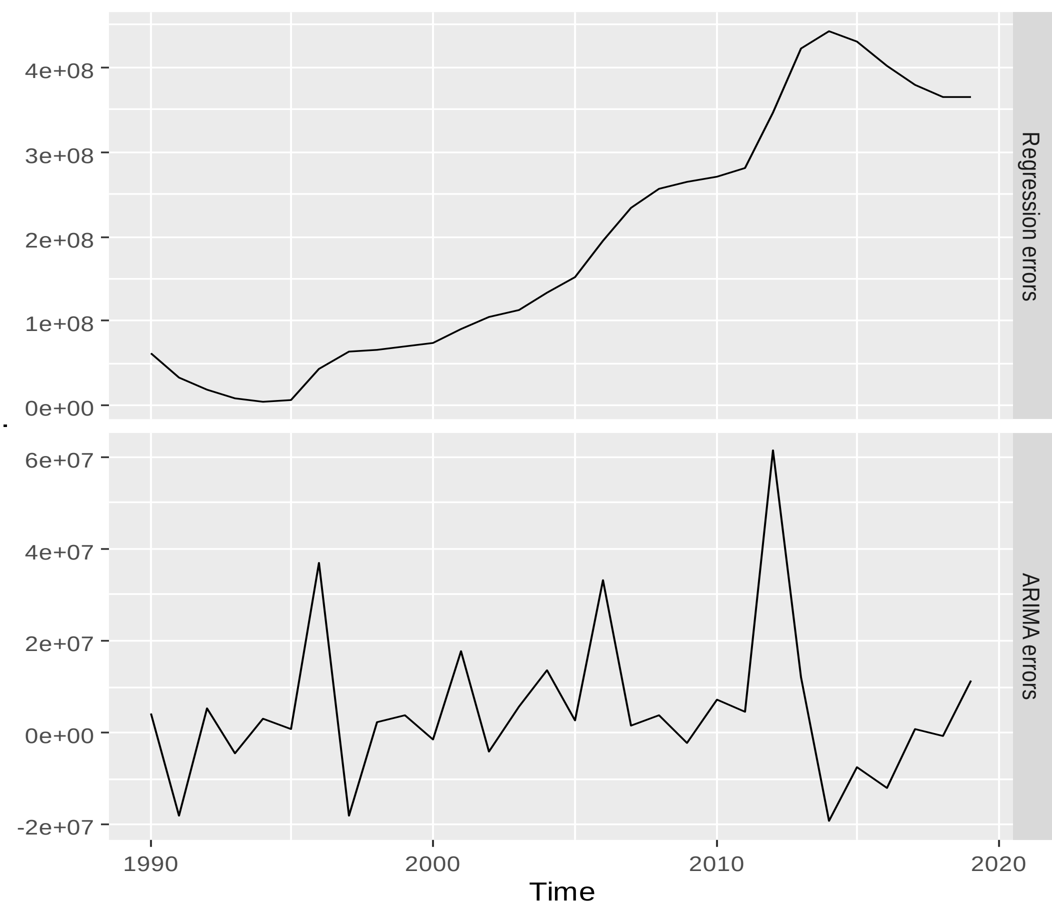

Figure 2. Regression errors and ARIMA errors from

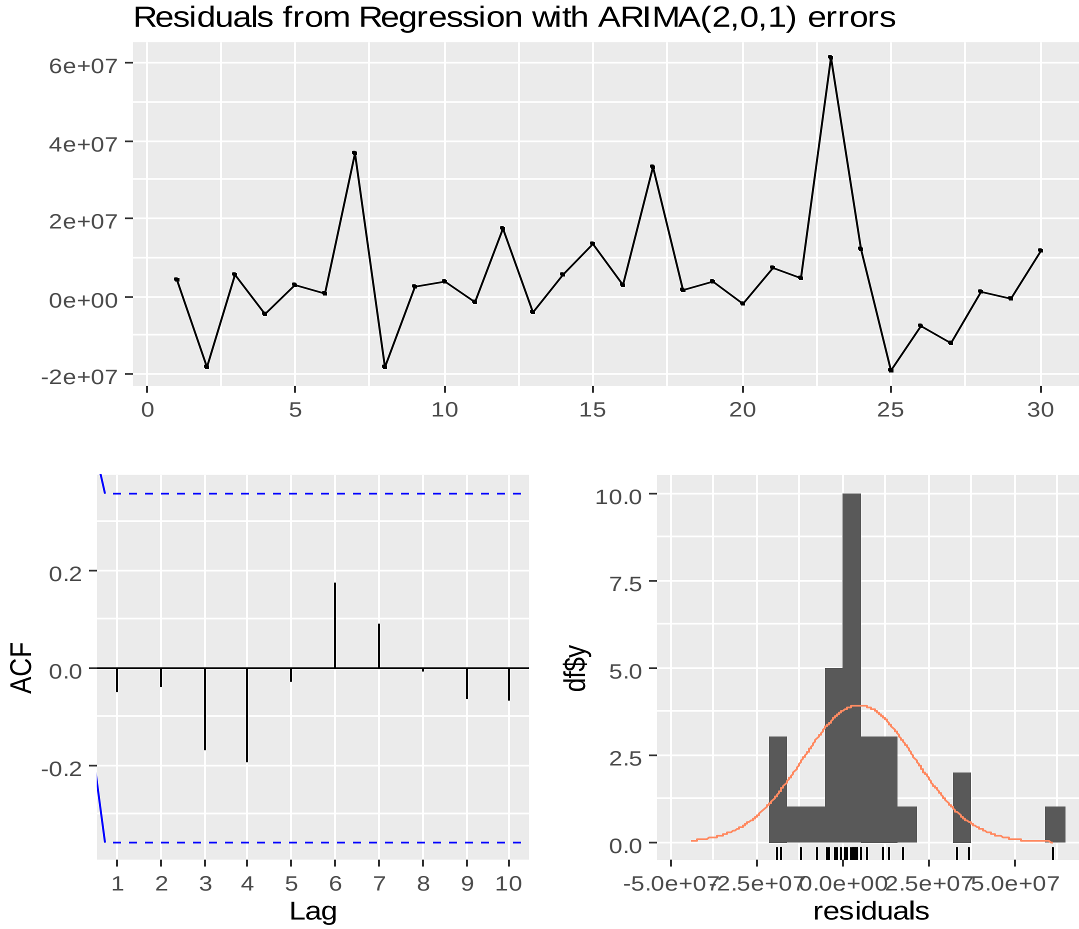

Figure 3. Adequacy check for regression model with ARIMA(2,0,1) errors

Figure 3 shows the time plot, ACF plot, and the histogram of the residuals of the regression model with ARIMA(1,0,0) errors. The time plot shows an evidence of constant variance, ACF plot shows that the errors are uncorrelated, and the histogram shows that the errors are normally distributed with mean zero. In Table 3, the Ljung-Box test statistic is 4.5408 and p-value is 0.2087, which is greater than 0.05, therefore, the forecast errors produced by Regression with ARIMA(2,0,1) errors are uncorrelated, which implies that the selected model is adequate.

Table 3. Ljung-Box test for regression model with ARIMA(2,0,1) errors

Ljung-Box test
data: Residuals from Regression with ARIMA(2,0,1) errors Q* = 4.5408, df = 3, p-value = 0.2087

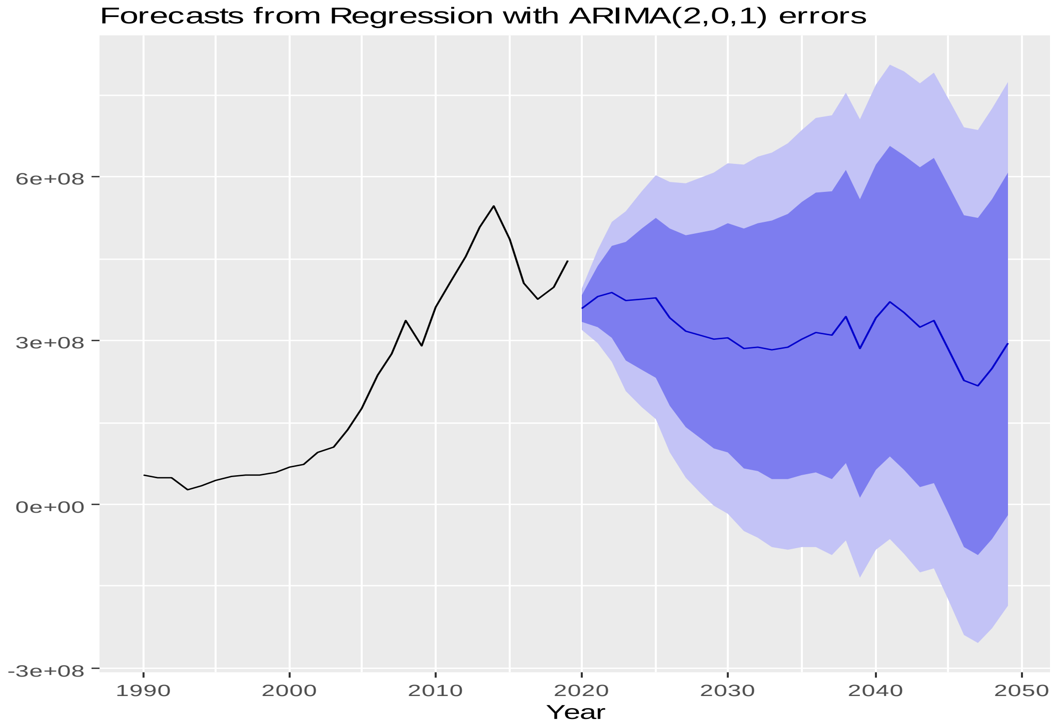

Figure 4. Forecast for 30 years ahead using regression model with ARIMA(2,0,1) errors

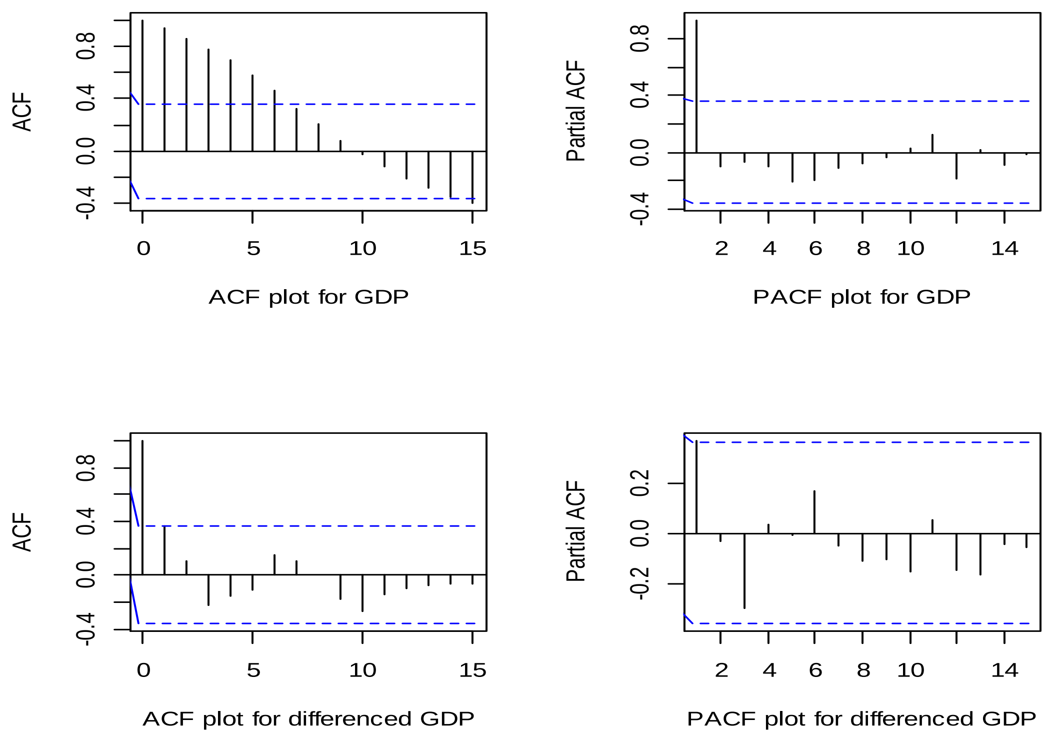

Figure 5. Estimated ACF and PACF plots for GDP and differenced GDP

ACF plot for GDP in Figure 5 shows a slow fall of the lags as the lag number increases (that is, it shows an exponential decay), which indicates that the GDP series is not stationary. while the ACF plot for differenced GDP shows a rapid fall of the lags as the lag number increases, which shows evidence of stationarity. This however indicates an AR model.

Table 4. ARIMA model selection

S/N	ARIMA Model	AICc
1	ARIMA(2,1,2) with drift	Inf.
2	ARIMA(0,1,0) with drift	1095.675
3	ARIMA(1,1,0) with drift	1093.835
4	ARIMA(0,1,1) with drift	1094.705
5	ARIMA(0,1,0)	1097.253
6	ARIMA(2,1,0) with drift	1096.511
7	ARIMA(1,1,1) with drift	Inf.
8	ARIMA(2,1,1) with drift	Inf.
9	ARIMA(1,1,0)	1093.147

10	ARIMA(2,1,0)	1095.634
11	ARIMA(1,1,1)	1095.640
12	ARIMA(0,1,1)	1094.930
13	ARIMA(2,1,1)	1097.310

ARIMA(1,1,0) in Table 4 has the lowest Akaike Information Criterion Corrected (AICc) of 1093.147, however, it is considered the best ARIMA model among the others for forecasting the Nigeria's GDP. The estimated coefficients of the selected model ARIMA(1,1,0) are shown in Table 5.

Table 5. Estimated coefficients of ARIMA(1,1,0) with non-zero mean

	ar1	
	0.4509	
Standard Error (se)	0.1664	
Sigma^2 = 1.211e+15: log likelihood = -544.340		
AIC = 1092.69	AICc = 1093.15	BIC = 1095.42

The estimated ARIMA(1,1,0) is written as

$$y_t = 0.4509 y_{t-1} + \varepsilon_t \tag{11}$$

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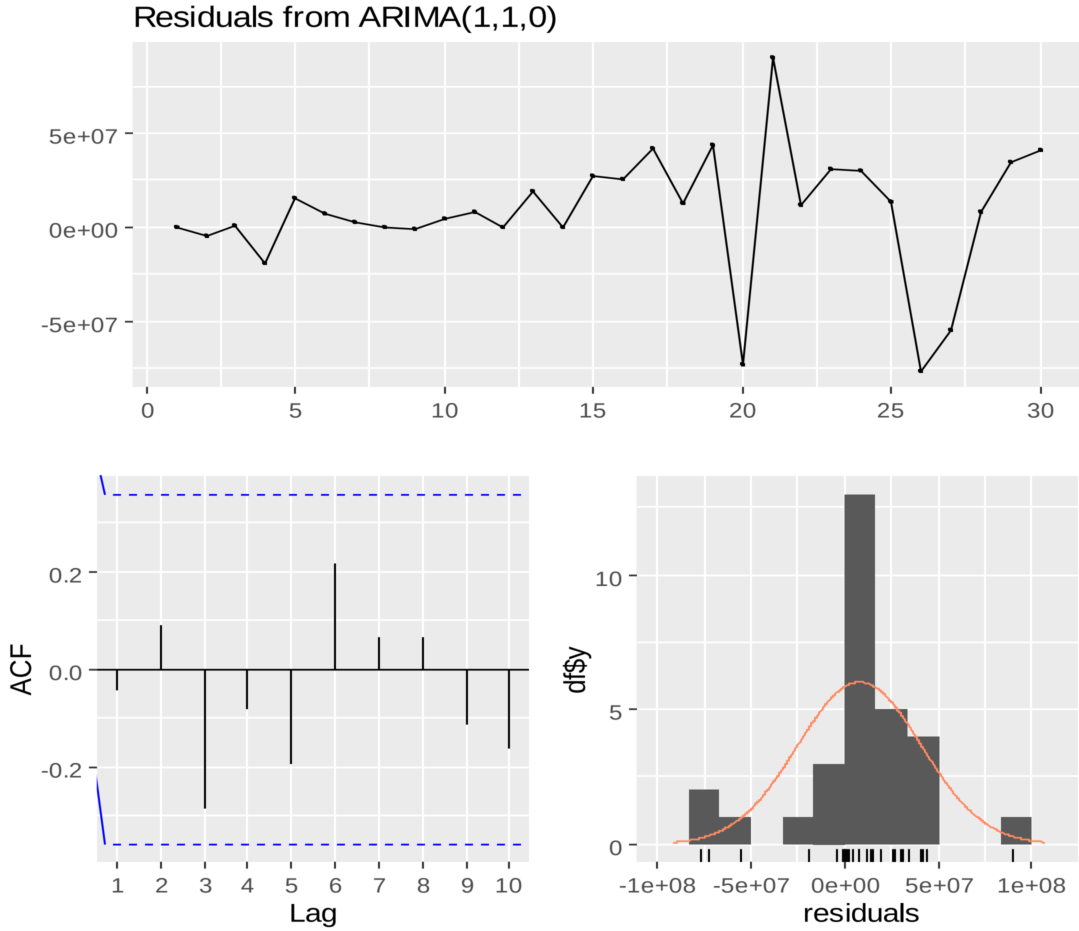

Figure 6. Adequacy check for ARIMA(1,1,0)

The residual plot in Figure 6 shows that the variance of the forecast errors is constant over time. The histogram of the residuals shows that the forecast errors are normally distributed, while the ACF plot of the residuals shows that the forecast errors are uncorrelated. The Ljung-Box test statistic in Table 6 is 6.7671 and p-value is greater than 0.05, and this shows that there is non-zero autocorrelation in the in-sample forecast errors. With all these assumptions met, therefore, ARIMA(1,1,0) is adequate for forecasting.

Table 6. Ljung-Box test for ARIMA(1,1,0) with non-zero mean

Ljung-Box test
data: Residuals from ARIMA(1,1,0)
Q* = 6.7671, df = 5, p-value = 0.2385

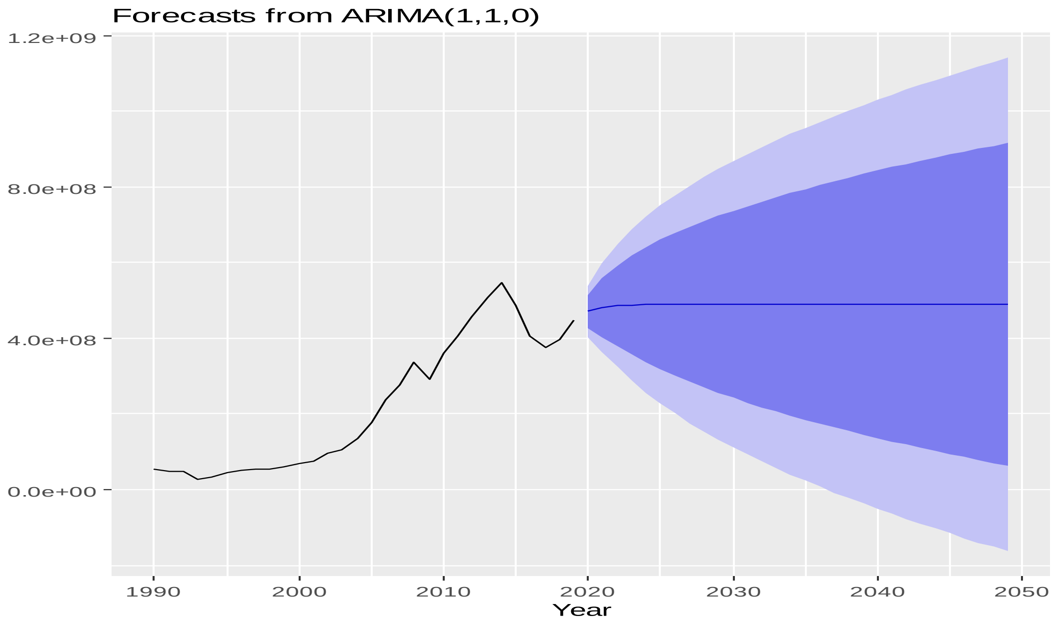

Figure 7. Forecast for 30 years ahead using ARIMA(1,1,0) for Nigeria's GDP

Table 7. Comparing regression with ARIMA(2,0,1) errors and ARIMA(1,1,0)

Models	Measures of Accuracy			
	RMSE	MAE	MAPE	MASE
Regression with ARIMA(2,0,1) errors	16776915	10645946	9.717476	0.3513025
ARIMA(1,1,0)	33620137	23352537	12.57867	0.7706036

The regression model with ARIMA(2,0,1) errors in Table 7 has the least RMSE, MAE, MAPE, and MASE compared to the ARIMA(1,1,0). However, regression model with ARIMA(2,0,1) errors is considered the appropriate model for forecasting Nigeria's GDP.

CONCLUSION

The aim of this paper is to find out between the two linear models Regression with ARIMA errors and ARIMA that can best forecast Nigeria's GDP, using annual data from 1990 to 2019. The application of Box-Jenkins is used to select the best ARIMA models, while the combination of least square methods and Box-Jenkins method is used to select the best regression model with ARIMA errors. The best model for forecasting Nigeria's GDP is selected using the evaluation of four measures of forecast accuracy. This paper shows that the best fit model for forecasting Nigeria's GDP is the Regression with ARIMA(2,0,1) errors.

However, with the current situation of oil price reduction in the world market, and the recent inflation in Nigeria, and devaluation of Naira, this paper presents quantitative model for policy makers in Nigeria towards economy growth. The significance of this paper is also evident in carrying out further research by analyzing the implementation of policies in Nigeria based on the current issues in Nigeria, and the world issues, in order to achieve and implement the United Nations Sustainable Development Goals (SDGs).

REFERENCES

Bing Yang, Chenggang Li, Min Li, Kang Pan, Di Wang. (2016). Application of ARIMA model in the prediction of the Gross Domestic Product. *Advances in Intelligent Systems Research*, 130: 1258-1262.

Dritsaki, C. (2015). Forecasting Real GDP Rate through Econometric Models: An Empirical Study from Greece. *Journal of International Business and Economics*, 3: 13-19.

Hyndman, R. J. and Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting.* 22(4): 679-688.

Jama, Mohamed. (2020). Time Series Modeling and Forecasting of Somaliland Consumer Price Index: A Comparison of ARIMA and Regression with ARIMA Errors. *American Journal of Theoretical and Applied Statistics,* 9(4): 143-153.

Maity, B. and Chatterjee, B. (2012). Forecasting GDP growth rates of India: An Empirical Study. *Internal Journal of Economics and Management Sciences,* 1(2012): 52-58.

Malgorzata Murat, Iwona Malinowska, Magdalena Gos, and Jaromir Krzyszczak. (2018). Forecasting daily meteorological time series using ARIMA and regression models. *International Agrophysics*, 3: 253-264.

Noura, Eissa. (2020). Forecasting the GDP per Capita for Egypt and Saudi Arabia Using ARIMA Models. *Research in World Economy*, 11(1): 247-258.

Rupesh K. J., Ambuj, K. A. and Ashok, K. S. (2020). Envisaging the Road Accidents using Regression Analysis. *International Journal of Advanced Science and Technology*, 29(5s): 1708-1718.

Uwimana, A., Xiuchun, B. I., & Zhang, S. (2018). Modeling and Forecasting Africa's GDP with Time Series.

Van den Bossche, F., Wets, G. and Brijs, T. (2007). A regression model with ARIMA errors to investigate the frequency and severity of road traffic accidents.

Wabomba, M. S., Mutwiri, M. P., and Fredrick, M. (2016). Modeling and forecasting Kenyan GDP using autoregressive integrated moving average (ARIMA) models. *Science Journal of Applied Mathematics and Statistics*, 4(2): 64-73.

Youssef, J., Ishker, N., and Fakhreddine, N. (2021). Economic Forecast of the Wealthiest Gulf Countries Using ARIMA Model. *Journal of Applied Economic Sciences*, 2(72): 228-237.