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ARIMA Model and its Application to Budget Performance

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Abstract

In Time Series Analysis, the Autoregressive Integrated Moving Average model, has been applied to model different phenomena. Financial budget performance and classification of functions of government performance have not been modeled simultaneously in literature. In this study, a class of statistical time series models was examined in analyzing and forecasting the budget performance of Lagos State for the period under study (1968–2018). Also, it examined the trend of the Classification of Functions of Government (COFOG) in Lagos State (2008–2018). Box-Jenkins' ARIMA and ARMA models' approaches were used in this study. The financial budget performance was differenced to obtain stationarity. The best model chosen based on the selection criteria, Akaike Information Criterion (AIC) is ARIMA (1,1,1). The series presented for the classification of functions of government was stationary over time and the pattern indicated the volatility nature of their performance. A unit root test was conducted to ascertain the degree of stationarity. The forecast results suggested that the financial budget would continuously increase at the rate of approximately 3% on the average yearly for next ten years; and an increment of approximately 0.24% within the classification of functions of government for the next ten years.

Keywords: ARIMA Model; Budget Performance; COFOG; Stationarity; Time Series

1. Introduction

In Applied Statistics, time series, as a tool, has been used for making predictions since ARIMA model was developed. The ARIMA model was first proposed by Box and Jenkins in 1970. The fact that this model simply has few parameters makes it superior to other time series models. The classical ARIMA model uses backshift operators and the *d*th difference to operate in time series. It is usually of order *p*, *q*. The complete ARIMA approach, including how to handle seasonal time series within a generalized ARIMA, has been described in detail (see Box & Jenkins, 1970). However, the benefits of using the models have been summarized and proved by the application of ARIMA in many fields (see Adebayo et al., 2014; Carlson et al., 1970; McKerchar & Delleur, 1974; McMichael & Hunter, 1972; Padhan, 2012).

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In order to represent the monthly sequences of flow, McKerchar and Delleur (1974) applied the seasonal ARIMA model to 16 series of monthly flows for rivers that are tributaries to the lower Ohio river in the United States. The multiplicative seasonal ARIMA model fitted was in the order of (2,0,0) (0,l,l). The ARIMA model fitted for the series required 27 parameters and the latter required only four parameters. Majority of quantitative forecasting at the local government level is probably done using trend analysis or simple moving averages (Frank and Zhao, 2009). The objective of the study will follow the ARIMA modelling. ARIMA model has been a very effective tool in the study or analysis of budget for government, corporate and private organization (Congressional Budget Office, 2011).

Seneviratna and Shuhua (2013) investigated the use of the univariate time series ARIMA model to predict the rates of government twelve-month Treasury bills in Sri Lanka between June 2008 and June 2013. Four models were primarily constructed using the Box Jenkins methodology, and several diagnostic tests and selection criteria were utilized to determine which model was most appropriate. The forecasted values' accuracy was compared with other models using Mean Squared Error (MSE) and Mean Absolute Error (MAE) criteria. The empirical findings demonstrate that ARIMA(1,1,2) is the best model for the twelve-month Treasury bills. The developed model was used to forecast the next five weeks, and the findings revealed that the Treasury bill rates were slowly declining. The decline in interest rates suggests a significant increase in the interest paid on government Treasury bills. Therefore, the study's findings have influenced investors' future investment planning in some way. Some nations and large subnational jurisdictions use simulations or systems of statistical models to forecast their economies and related budgetary data (New York City Office of Management and Budget, 2016). It has been effective in predicting economic (Petrica et al., 2016), marketing (Yan and Chen, 2018), industry production (Mgaya, 2019), and so on.

The process $\{Y_t\}$ is referred to as an ARIMA (p, d, q) if its d^{th} difference is an ARMA (p, q) process. i.e., if $X_t = \nabla^d Y_t$, then the process is called an ARMA (p, q) process. We can examine the first order difference process if the original process $\{Y_t\}$ is not stationary; $X_t = \nabla Y_t = Y_t - Y_{t-1}$ or the second order differences and soon. The ARIMA model's forecasting results could include forecasted values as well as upper and lower limits. A (1- α) confidence interval is provided by upper and lower limits. Since α is the specified confidence, any realization that lies within the interval will be accepted. In contemporary statistical theory, forecasting the economic budget can be done in a variety of ways. The majority of them deal with time series forecasting without any additional data, i.e., without considering the effects of other variables.

One such approach is to build an ARIMA $\{Y_t\}$ model. Its core idea is that while some time series is a collection of time-dependent random variables, changes in the entire time series follow a set of rules that can be modeled by the related mathematical equation $X_t = \nabla Y_t = Y_t - Y_{t-1}$ (first order difference) or $X_t = \nabla^2 Y_t = \nabla(\nabla Y)_t = Y_t - 2Y_{t-1} + Y_{t-2}$ (second order difference) and so on. One can obtain the best prediction values and a deeper understanding of the time series' structure and characteristics by evaluating the mathematical model. Depending on the type of analysis and a practical requirement, time series observations are regularly found in many different fields.

This study, however, is aimed at examining a class of statistical models in analyzing and forecasting the budget performance for the period under study of the financial budget in Lagos State between the period 1968 and 2018 and examining the time plot of the series of the Classification of Functions of Government (COFOG) performance in Lagos State between 2008 and 2018. The COFOG performance in Lagos state is a measurable variable. The degree of stationarity of the data will be examined as well as fitting a statistical model suitable for forecasting the data. This research work will help to identify the regular components of the data i.e., the trend and seasonal components and to check if there are any the random movements. It will help to inquire if the data is a seasonal time series or a time series without seasonal component. It will also help to examine the data and see if there is any irregularity or fluctuations in order to find it and subtract it away (by splitting the residual up on our plot) from a data analytical perspective.

The findings of this study will benefit Lagos state government for evolving means/strategies to rigorously monitor the implementation and the performance of her budgets by making various provisions in the budget to improve public service, enhance security of life and property, improve access to health facilities and enhance accountability and transparency in order to propel growth in the economy. This study will also expose much in terms of seasonality.

2. Materials and Methods

The selection of a proper model is crucial as it captures the fundamental structure of the series, and the fitted model is then used to predict the future. Time series are used for various purposes. The goal may be to control the process that produces the series, it may be to understand the mechanism generating the series, or it may be to simply obtain a concise description of the key aspects of the series. The goal may also be to forecast the future using knowledge of the past. Among the time series components are trend, seasonal movement, cyclical movement, irregular movement and outliers. The initial step in analyzing a time series data is to examine the trend by observing the time plot. This will highlight the key characteristics, including the trend, seasonality, discontinuity, and outliers. (Chatfield, 1996)

2.1 Time Series Process

White Noise:

Let $\{\mathcal{E}_t\}$ be white noise with zero mean [E($\mathcal{E}_t$)=0], constant variance [V($\mathcal{E}_t$) $=\sigma^2$], and uncorrelated random variables [E($\mathcal{E}_t\mathcal{E}_s$) = 0]. The scatter plot of a random series plotted against time will depict an irregular pattern and it becomes impossible to forecast the future values of such a series.

Autoregressive Model:

In autoregressive (AR) model, Y_t depends only on its own past values Y_{t-1}, Y_{t-2}, …, Y_{t-p}, where p is the number of time period available. Thus, $Y_t = \text{f}(Y_{t-1}, Y_{t-2}, Y_{t-3}, \dots, \mathcal{E}_t)$

A typical illustration of an AR model where it depends on p of its past values known as AR(p) model is represented below:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \ldots + \beta_p Y_{t-p} + \mathcal{E}_t \quad (2.1)$$

Moving Average Model:

In a moving average model, Y_t only depends on the random error terms (ε_t) and it is a white noise process. i.e. Y_t= f(ε_t, ε_{t-1}, ε_{t-2}, ε_{t-3}, …). A typical illustration of this model, where the observations, Y_t depends on q of its past values is called a MA(q) model and is represented by

$$Y_t = \beta_0 + \varepsilon_t + \phi_1\varepsilon_{t-1} + \phi_2\varepsilon_{t-2} + \phi_3\varepsilon_{t-3} + \ldots + \phi_q\varepsilon_{t-q} \quad (2.2)$$

The error ε_t terms are assumed to be white noise processes with mean zero and variance σ^2.

Invertibility

An MA(1) model is given by $Y_t = e_t - \theta_1 e_{t-1}$ The model is said to be invertible if $|\theta_1| < 1$, since it is possible to rewrite the model into an infinite – order autoregressive model.

$Y_t = (-\theta Y_{t-1} - \theta^2 Y_{t-2} - \theta^3 Y_{t-3} - \ldots) + e_t$ through iterative means.

2.2 Mixed Models

2.2.1 Autoregressive Moving Average Models (ARMA):

In ARMA model, AR and MA models are combined to form a hybrid model called mixed autoregressive/moving average (ARMA) model. A mixed model is a model that contains both AR and MA components.

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \phi_P Z_{t-P} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q} \quad (2.3)$$

Z_t is called mixed models i.e., ARMA (p, q). The simplest autoregressive moving average model is ARMA (l, l) and it is given by: $Z_t - \phi_1 Z_{t-1} = \theta_1\varepsilon_{t-1}$

ARMA models have the properties examined for AR and MA models, hence stationary and invertible holds respectively if the roots of the polynomials lie outside the unit circle. Given the number of parameters, the ARMA model has a greater capacity for approximation than AR and MA models. It can be thought of as a general model that includes AR and MA models as special cases.

Box and Jenkins (1976) suggested a three-step ARMA modeling process:

(i) Identifying the particular ARMA model: It has three formations which are Autocorrelation function (ACF), Partial autocorrelation function (PACF) and Inference from ACF and PACF.

(ii) The estimation of parameters.

(iii) The checking of the model (Diagnostic checking).

Time series data must be stationary in order to fit an ARMA model, which means that the mean and variance of the data must not change consistently over time. The fact that an ARMA process uses fewer parameters than a pure MA or AR process by itself is one of its benefits. Due to the thorough explanation of these models in Box and Jenkins (1976) the ARMA (p,q) processes are also commonly referred to as stationary non-seasonal Box-Jenkins processes. There are numerous ways to detect ARMA models, and each one ultimately relies on the extended Yule-Walker equations.

Autoregressive Moving Average (ARMA) Models for Stationary Time Series

The primary concept of stationarity in this model is that the probability laws that govern the behaviour of the process and the mean do not change over time. A series $\{ Y_t\}$ is said to be stationary, if the joint distribution of $Y_{t1}\, Y_{t2}, \dots, Y_{tn}$ is the same as the joint distribution of $Y_{t1-k}\, Y_{t2-k}, \dots, Y_{tn-k}$ ∀ t_i, i = 1, 2,…, k and for all choices of time lag k. White noise is a good illustration of a stationary process.

Assuming the observed time series $\{ Y_t\}$ is partly autoregressive and partly moving average, the model for the series is generally represented by

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \qquad (2.4)$$

The process (Y_t) is said to be a mixed ARMA process of orders p and q i.e. ARMA (p, q). A special case is ARMA (1,1).

ARMA (1,1) Model

The ARMA(1,1) model is given by

$Y_t = \varphi Y_{t-1} + e_t - \theta e_{t-1}$ with variance given by $\gamma_0 = \frac{(1-2\theta\varphi+\theta^2)\sigma/e^2}{1-\varphi^2}$ and autocorrelation function given by $\rho_k = \frac{(1-\theta\varphi)(\varphi-\theta)}{1-2\theta\varphi+\theta^2}\varphi^{k-1}$ for $k \geq 1$

The autocorrelation function decays exponentially as the lag increases, where φ is the damping factor, but the decay starts from initial value ρ_1, which is dependent of θ as well. This, however, negates the AR(1), which also decays with damping factor φ but always start from the initial value ρ_0= 1, and the stationarity condition model is |θ|<1.

Differencing

Differencing is a way of rendering series stationary, that is, without trend. The first difference operator is defined by:

$$\nabla Y_t = Y_t - Y_{t-1} \qquad (2.5)$$

And can be written as: $\nabla Y_t = (1-B)Y_t$

$$B^j Y_t = Y_{t-j}, \qquad (2.6)$$

So that

$$BY_t = Y_{t-1}\ , \qquad (2.7)$$

where B is called the Backshift Operator. If the first difference of a series does not induce stationarity, then another difference is taken.

$$\begin{aligned}\nabla^2 Y_t &= \nabla\,(\nabla Y_t)\\ &= \nabla\,(Y_t - Y_{t-1})\\ &= \nabla Y_t - \nabla Y_{t-1}\\ &= Y_t - Y_{t-1} - Y_{t-1} - Y_{t-2}\\ &= Y_t - 2Y_{t-1} - Y_{t-2}\end{aligned}$$

and can be written as

$$\nabla^2 Y_t = (1-\mathrm{B})^2 Y_t, \qquad (2.8)$$

where B is the Backshift Operator.

Usually, differencing one or two times renders the series stationary. For a multiplicative model, dividing the original series by the fitted trend will yield a series without trend. For an additive model, subtracting the fitted trend from the original time series will yield a series without trend.

2.2.2 Autoregressive Integrated Moving Average (ARIMA) Models

In ARIMA model, the autoregressive component along with the error term's past values, are used to represent the current values of a time series (the moving average terms). To induce stationarity, a series must be differenced a certain number of times, which is referred to as the integrated component. In ARIMA model, the number of times a time series is differenced to induce stationarity is denoted by d, thus, ARIMA(p, d, q), where p represents the number of autoregressive parameters, d stands for the number of series differences required to achieve stationarity, and q denotes the number of moving average parameters.

It may be represented as; $\theta(B)\theta(B)\nabla^d \nabla_s^d y_t = \theta(B)\ \theta(B)\ a_t$;

Where, $x_t = \nabla^d \nabla_s^d y_t$ is a stationary series, $\nabla = 1 - B$ is a Difference operator.

$$\nabla^d = (1 - B)^d \qquad (2.9)$$

represents the number of regular differences.

$\nabla_s^d y_t$ represents the number of seasonal differences required to induce stationary in y_t.

ARIMA (p, d, q) can also be written as:

$\theta(B)\ (1 - B)^d\ Z_t = \Theta(B) e_t$; where Z_t is an ARIMA(p,d,q) process if $(1 - B)^d\ Z_t$ is ARMA(p,q) and there is some white noise e_t .

Equation (2.9) can be written as;

$$\phi(B)\ \nabla^d = \Theta(B) e_t \text{ using the difference operator } \nabla^d \qquad (2.10)$$

where B is the Backshift operator

3. Results and Discussion

This study is based on the application of some of time series techniques with reference to the data collected for financial budget over a period 50 years ranging from 1968 to 2018 and for classification of functions of government in Lagos state over a period 10 years ranging from 2008 to 2018.

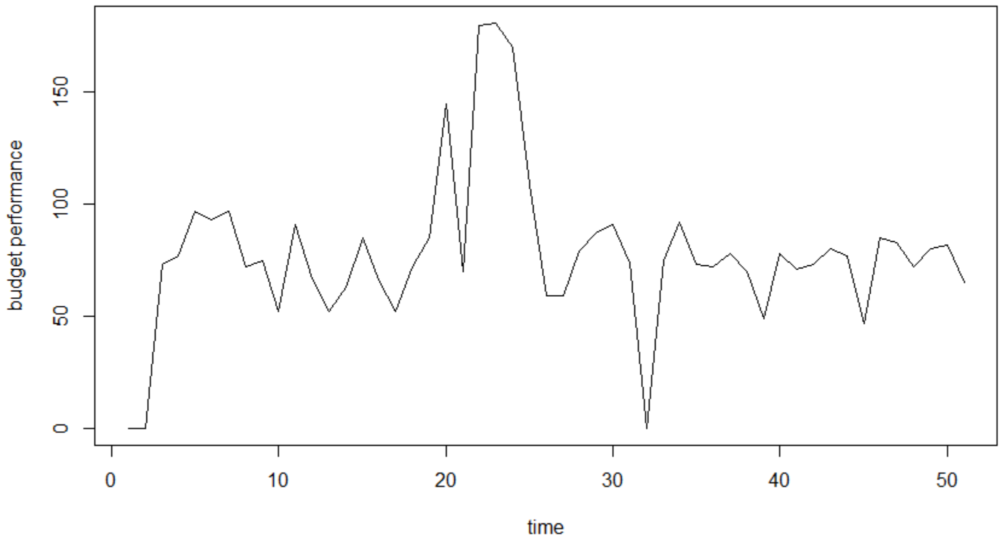

Figure 3.1: Time Plot of Financial Budget Performance

Figure 3.1 shows a nonstationary series. The series can be described using an integrated term by differentiating the process (differencing) in-order to make the series stationary. The time plot shows the presence of trend and seasonality in the series. However, the Financial Budget Performance of Lagos state reach a peak in 1992 (24^{th} point) and the lowest is in 2000 (32^{nd} point).

3.1 Stationary Test for Budget Performance

3.1.1 ADF Test

H_O: There is Unit Root

H_1 : There is No Unit Root

Table 3.1: Unit Root Test

Process	Test Statistics	Lag Order	P-value
ADF	-2.8831	3	0.2193

Table 3.1 shows that p-value $> \alpha = 0.05$, we do not reject null hypothesis and that there is a unit root, hence the series is not stationary.

3.1.2 KPSS Test

H_O: The series is not stationary.

H_1 : The series is stationary.

Table 3.2: KPSS Level

Process	Test Statistics	Lag order	P-value
KPSS	0.1249	3	0.1

Table 3.2 shows that the p-value $> \alpha = 0.05$, we do not reject null hypothesis and conclude that series is not stationary.

3.2 Model Identification for Financial Budget

The model for the financial budget performance in Lagos state is done by estimating the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The selection of a tentative time series model is frequently accomplished by matching estimated autocorrelations with the theoretical autocorrelation.

Table 3.3: Sample ACF and PACF of the Budget Performance

Lag k	ACF	PACF	AIC
0	1.000	0.000	12.029683
1	0.490	0.490	0.000
2	0.229	-0.015	1.988194
3	0.058	-0.063	3.783201
4	0.017	0.021	5.761244
5	-0.039	-0.055	7.606465
6	-0.037	0.003	9.606081
7	-0.069	-0.053	11.464314
8	-0.133	-0.106	12.887789
9	-0.144	-0.037	14.819504
10	-0.204	-0.134	15.889175
11	-0.004	0.208	15.636443
12	-0.076	-0.186	15.846971
13	0.019	0.120	17.106024
14	-0.032	-0.096	18.632995
15	0.036	0.077	20.332601
16	0.029	-0.008	22.329050
17	0.000	-0.081	23.993976

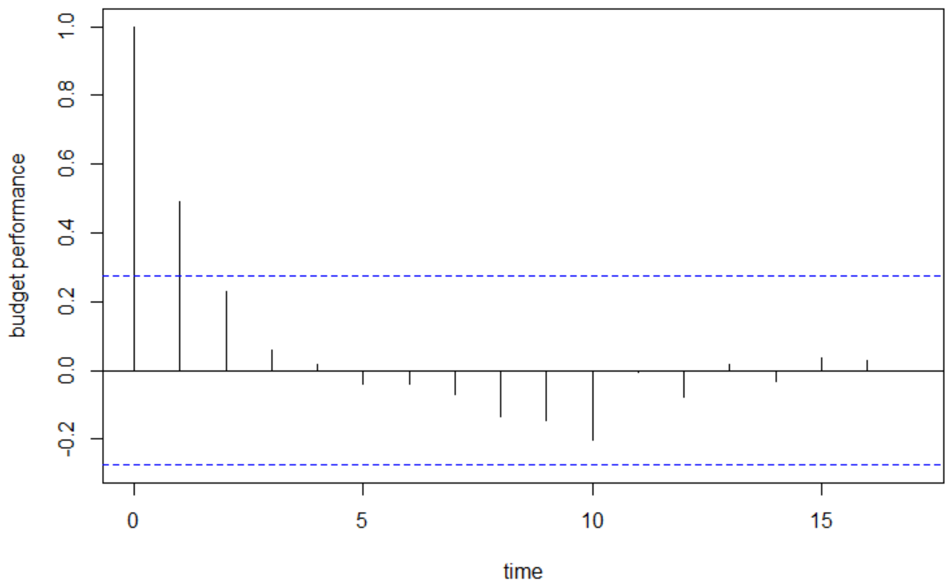

Figure 3.2: The ACF of the budget performance

Table 3.3 shows that the Autocorrelation function (ACF) of the budget performance at Lag1 is 0.490, which corresponds to the Partial Autocorrelation Function (PACF) at Lag1, as shown in Figures 3.2 and 3.3.

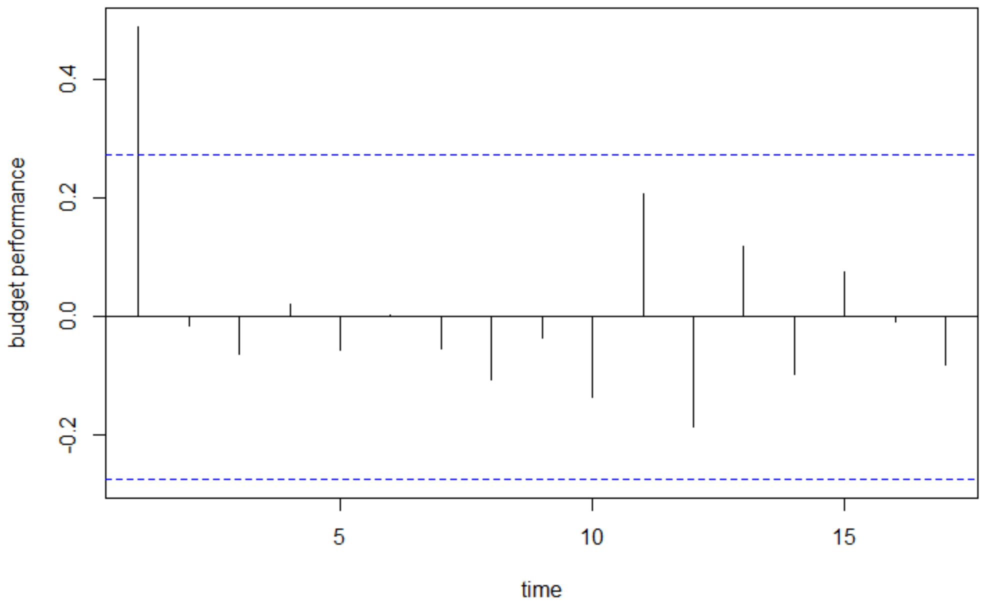

Figure 3.3: The PACF of the budget performance

3.3 Parameter Estimation

To identify the best fitted model among several linear and nonlinear time series models, the Akaike information criterion (AIC) (Akaike 1974) was used. This criterion measures the deviation of the fitted model from the actual one. The model with the minimum value of AIC which is the contending models was chosen.

Table 3.4: Estimation of the ARIMA Model

	ARIMA (1,0,0)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (2,0,0)	ARIMA (2,1,0)	ARIMA (2,1,1)	ARIMA (2,2,2)	ARIMA (2,2,3)	ARIMA (2,2,4)
A.R	0.5362	-0.2630	0.5708	0.5252	-0.2847	0.5493	0.5181	-0.0625	-0.0903
S.E	0.1240	0.1351	0.1301	0.1406	0.1407	0.1441	NAN	0.3698	1.0588
A.R				0.0244	-0.0794	0.0525	0.0642	0.4052	0.3255
S.E				0.1481	0.1461	0.1523	0.1410	0.2536	0.7069
M.A			-1.000			-1.000	-1.8510	-1.2734	-1.4067
S.E			0.0772			0.0754	0.0473	0.4380	1.0797
M.A							0.8566	-0.2117	0.0515
S.E							NAN	0.8186	2.0226
M.A								0.4938	0.3076
S.E								0.4030	1.0969
M.A									0.0658
S.E									0.2362
Intercept	75.9702			75.7960					
S.E	8.7532			9.0621					
Estimated Sigma Squared	868.6	1031	886.4	868.1	1024	886.4	991	984	983.1
Log likelihood	-245.09	-244.43	-241.97	-245.08	-244.28	-241.91	-241.08	-240.9	-240.77
AIC	496.18	492.86	489.94	498.16	494.56	491.82	492.16	493.8	495.53

From the Table 3.4, we fitted ARIMA(p,d,q), where p is the number of autoregressive parameters, d is the number of differencing and q is the number of moving average parameters. . The best model chosen based on the minimum Akaike Information Criterion (AIC) is ARIMA (1,1,1). Thus, the ARIMA model is written as:

$$Y_t = 0.5708\, Y_{t-1} - 1.000\, e_{t-1} + e_t \tag{2.11}$$

Kwiatkowski Philips Schmidt Shin (KPSS) and Bayesian Information Criterion (BIC) tests are other criteria that can be used to decide on the model.

3.4 Box- LJung Test

Here, the Box-LJung test is tested to check whether the residuals are correlated or not.

H_O: The residuals are uncorrelated.

H_1 : The residuals are correlated.

Table 3.5: Test Statistics

Process	Box test	Df	P-value
Budget performance	0.20379	1	0.6517

Table 3.5 shows that the p-value $> \alpha = 0.05$, so we do not reject null hypothesis and conclude that the residuals are uncorrelated. Hence the model fits the data.

3.5 Forecast Evaluation for Budget Performance

This is an out-of-sample forecast values in predicting the budget performance in Lagos state for the next ten years (2019-2028). The predicted values of the table below contain an increasing order of the financial budget performance.

Table 3.6: Forecast Evaluation 1

S/n	Financial year	Percentage Performance
1	2019	32
2	2020	38
3	2021	42
4	2022	45
5	2023	47
6	2024	49
7	2025	51
8	2026	53
9	2027	55
10	2028	56

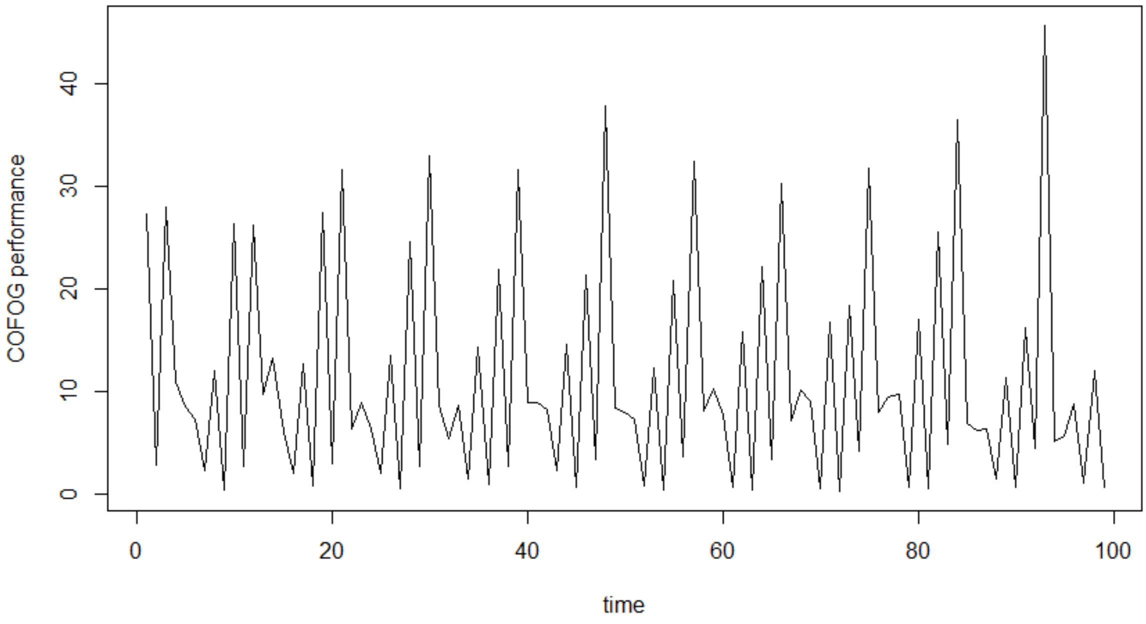

Figure 3.4: Time Plot of COFOG Performance

Figure 3.4 shows that the various classification of government functions in Lagos state are stationary over time and there is some variability which indicate the volatility nature of their performance.

3.6 Stationary Test for (COFOG)

3.6.1 ADF Test and P-P Test

H_O: There is Unit Root

H_1 : There is No Unit Root

Table 3.7: Unit Root Test 2

Process	Test Statistics	Lag Order	P-Value
ADF	-7.206	4	0.01
P-P	-151.65	3	0.01

Table 3.7 shows that the p-value $< \alpha = 0.05$, thus, the null hypothesis is rejected and we conclude that there is no unit root. The process is stationary.

3.7 Model Identification for Classification of Function of Government (COFOG)

The model for the COFOG in Lagos state is achieved by plotting the estimated ACF and PACF against time. The matching of the estimated sample ACF and PACF of the underlying stochastic processes suggest that the series were stationary, using the ACF, PACF and AIC criteria.

Table 3.8: Sample ACF and PACF of the (COFOG)

Lag k	ACF	PACF	AIC
0	1.000	0.000	139.809353
1	-0.460	-0.460	118.255159
2	0.451	0.304	110.646892
3	-0.371	-0.122	111.172811
4	-0.079	-0.511	83.203928
5	-0.059	-0.100	84.207734
6	-0.404	-0.546	51.108897
7	-0.417	-0.065	52.689992
8	-0.432	-0.396	37.816683
9	0.862	0.575	0.000000
10	-0.425	0.029	1.914610
11	0.440	-0.128	2.288673
12	-0.344	-0.165	1.568573
13	-0.052	0.030	3.480966
14	-0.053	-0.056	5.167336
15	-0.362	0.107	6.033367
16	0.383	0.001	8.033313
17	-0.392	0.004	10.032025
18	0.767	0.049	11.797423
19	-0.390	0.067	13.357674

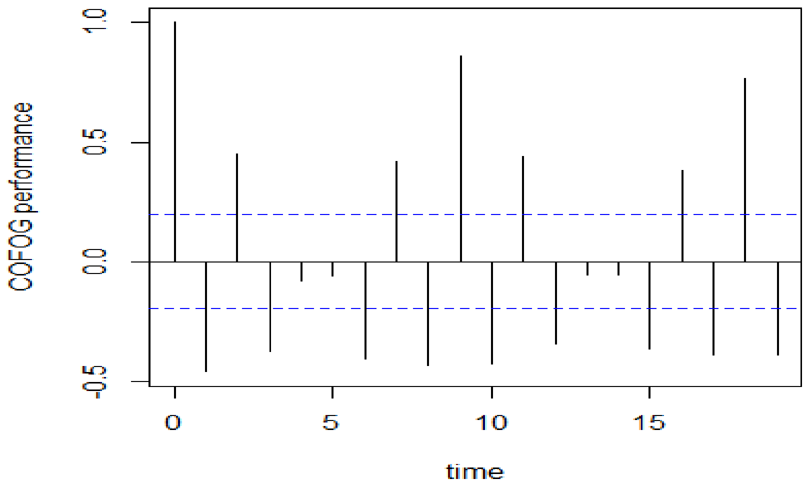

Figure 3.5: The ACF of the COFOG

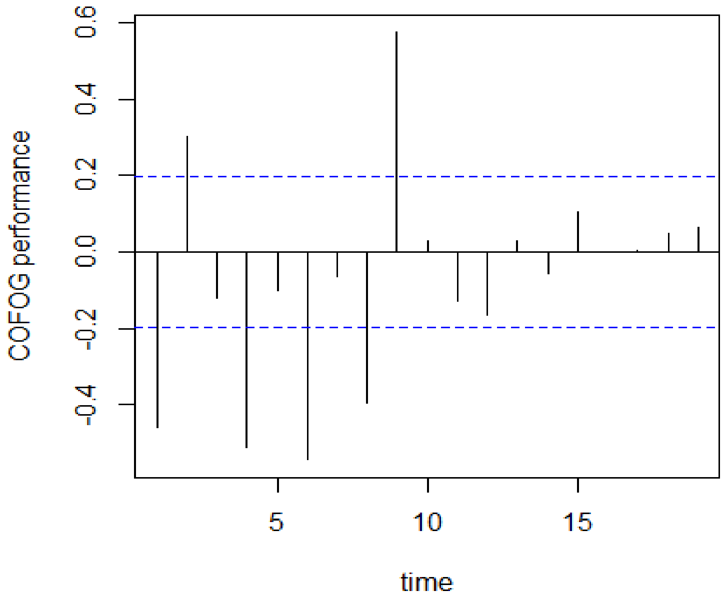

Figure 3.6: The PACF of the budget performance

Figure 3.5 shows that the Autocorrelation function (ACF) of the COFOG performance at Lag1 is -0.460 which corresponds to the Partial Autocorrelation Function (PACF) at Lag1 in Figure 3.6

3.8 Box- Ljung Test 2

H_O: The residuals are uncorrelated.

H_1 : The residuals are correlated.

Table 3.9: Test Statistics 2

Process	Box test	Df	P-value
COFOG %	0.15796	1	0.691

Table 3.9 shows that the p-value $> \alpha = 0.05$, so, we do not reject null hypothesis and conclude that the residuals are uncorrelated. Hence the model fits the data.

3.9 Forecast Evaluation for COFOG

This is an out-of-sample (long term) forecast values in predicting the COFOG performance in Lagos state for the next ten years (2019-2028). The predicted values of the table below contain an increasing order of performance of percentage allocated to each various classification of government in Lagos state.

Table 3.10: Forecast Evaluation 2

2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
8.97	10.70	11.11	11.94	13.31	15.22	17.62	20.45	23.65	27.18
9.28	10.76	11.17	12.06	13.49	15.46	17.91	20.79	24.03	27.59
10.12	10.77	11.25	12.19	13.68	15.71	18.21	21.13	24.41	28.01
10.26	10.82	11.33	12.33	13.88	15.96	18.52	21.48	24.80	28.42
10.50	10.84	11.41	12.48	14.09	16.23	18.83	21.83	25.18	28.84
10.53	10.89	11.51	12.63	14.30	16.49	19.14	22.19	25.58	29.27
10.64	10.93	11.60	12.79	14.52	16.77	19.46	22.55	25.97	29.69
10.64	10.99	11.71	12.95	14.75	17.04	19.79	22.91	26.37	30.13
10.70	11.04	11.82	13.13	14.98	17.33	20.12	23.28	26.78	30.56

4. Conclusion

Attempt had been made in the fitting an appropriate time series model for the data using both ARMA and ARIMA models. The descriptive and inferential procedures were conducted using R statistical package. The data was smoothed to average out irregular component before it was differenced. The data was subjected to ADF and Phillips-Perron unit root test. Hence a stationary test was conducted to affirm the degree of stationarity of the data at 5%, level of significance. From the sample ACF and PACF plots, it was seen that the financial budget (1968 – 2018) series followed autoregressive integrated moving average ARIMA (1,1,1) since the data was differenced once. The COFOG (2008 – 2018) series followed autoregressive moving average (ARMA) as it was stationary in the first place.

For the fact that the necessary technique was used in the analysis of data in pursuant of the objectives of the study, hence the main objectives of the study have been fully achieved. From the period under study (1968 – 2018) and (2008 – 2018) respectively for financial budget and

COFOG performance, it is easy to see that the process is a non-seasonal time series because it comprises both a trend component and an irregular component. Thus, the data was smoothed to make the trend component obvious in the plot. With the aid of differencing and performing Unit root test, the series becomes a Stationary time series. Forecast were made using Autoregressive Integrated Moving Average (ARIMA) Models because of its explicit statistical model for the irregular components of a time series and are defined for a stationary time series which the data is now one. In line with the conclusion of this study, the following recommendations were highlighted in order to improve the budget performance and the percentage allocation of classification of function of government in Lagos State.

We therefore recommend that the state government should put in place an effective database for the continuous collection and updating of the classification of function of government records which will prefer for the identification of area of key performance. Lagos state government should take appropriate measures for an efficient and effective allocation of the state's resources in planning subsequent budget based on the trend analysis of the classification of function of government performance. At the beginning of a financial year, Government should constitute a budget preparation committee to brainstorm on the budget performance and the economic situation. The department of budget should generate the necessary periodic performance data from all departments and units to enable it compare actual performance with budgeted figures. Budget execution should be done with work plans and cash forecast/budgets.

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