Domestic credit growth analysis using ARIMA technique; case study of Kenya

Abstract

The aim of this paper is to technically analyze domestic credit growth in Kenya using the Box -Jenkin framework. The first step involves model parameter identification. Unit root test show that domestic credit is stationary after the first difference. The ACF and PACF indicates cut off at lag zero in both cases. There are seasonal component in the ARIMA model. In the second step of model estimation, ARIMA(2,1,2)$(1,0,0)_{12}$ is obtained as the best fit for the sample period under consideration. Model diagnostics test in the third step, proves that there ARIMA modeling assumptions are met. The estimated model is used to forecast credit growth for the next twelve monthly values in year 2024 upto December. Its projected that domestic credit in Kenya will continue to growth fot the forecast horizon with percentage growth rate between 1.045 to 1.230 percent. The expected domestic credit value in December 2024 is 8.039 Trillions with a confidence interval from 7.389 to 8.746 Trillions.

Keywords and phrases

ARIMA Model, Box-Jenkins Methodology, domestic credit, Forecasting

1 Introduction

Domestic credit in any economy, is an important macroeconomic variable. Its plays an important role in allocating resources for investment in an efficient way. Credit from banks awarded to enterprenuer agents is used for productive investment where the agent did not have own fund. Investment demands and composition increase with increase in credit availability (Khamis and Klossifov [1]). The overall impact is increase in employment and output level within an economy. In credit development, the is likelihood of either a boom or bust. This may be attributed to several factors both internal and external. A credit boom is most likely caused by a higher share of external bank bond lending as an external factor(Avdjiev et al. [2]). Factors in the financial sector such as financial sector privatization, liberalization of the current account, sector comprehensive reforms and increased banking sector competition are attributed to increase in credit growth within an economy(Aydin [3], Hansen and Sulla [4], Coudert and Pouvelle [5], and Hauner [6])

Multivariate regression analysis of domestic credit and macroeconomic variables have carried out to determine key factors that contribute to domestic credit growth and the direction of the relationship. Domestic credit is positively affected by money supply growth, FDP growth, high degree of openness and increase in interest rates. On the other hand, macroeconomic variables such as gross capital formation and currency depreciation negatively affect domestic credit growth. (Islam [7], Sulaiman [8], Ndanshau and Semu [9]). The nexus between economic growth and domestic credit exhibit a significant positive relationship in Turkey and some Balkan countries(Alihodžić and Ekşï [10], Basha et al [11] and Wolde-Rufael [12]). There exists a significant causality between doemstic credit and economic growth, with the direction of the causal link varying from one country to another (Gozgor [13], Stolbov [14] and Bui [15]). Another important macroeconomic interaction is the international capital flows with domestic credit. Empirical research have proved that there exist a strong relationship between the two variables with capital inflow having a positive effect on domestic credit growth(Lane and McQuade [16], Di Giovanni et al. [17] and Igan et al. [18])

Uni-variate ARIMA approach and exponential smoothing has been used to model and forecast domestic credit. In Pakistan, Noreen et al. [19] observed that ARIMA (1,1,0) was a perfect fit for credit to private sector while ARIMA (3,2,3) fitted well in modelling credit to the public sector . Dinh [20] while analyzing and comparing China and Vietnam, observed that the best fit for Vietnam domestic credit was ARIMA (2,3,1) while in China it was ARIMA (2,3,5). Obeng-Amponsah [21] observed that exponential smoothing model with additive trend, multiplicative error and no seasonality was the optimal model to analyze and forecast Ghana domestic credit.

2 Methodology

2.1 Data

This study applied monthly banks domestic credit from January 2004 to December 2023. The data was obtained from Central Bank of Kenya (CBK) periodic statistical bulletins. A logarithm transformation is performed on the monthly domestic credit data to make the variance stable and reduce the effect outliers. From figure 1, there has been an increase in domestic over he sample period.

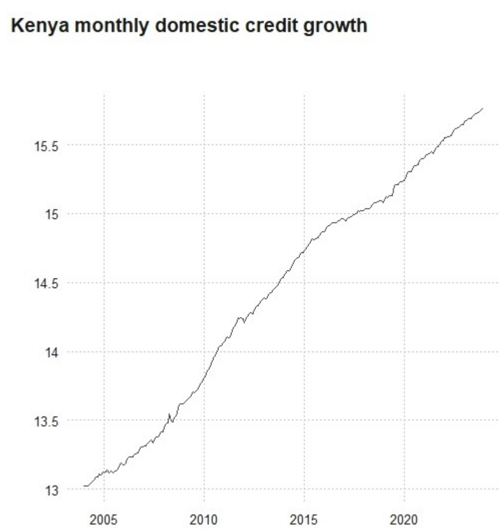

Figure 1: Monthly domestic credit plot

2.2 Model

2.2.1 Autoregressive (AR) Models

Consider a time series y_t that has an autoregerssive process of order p ie AR(p) expressed as;

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \tag{1}$$

For $t = 1, 2, \ldots, T$ and $\varepsilon_t \sim IID(0, \sigma^2)$ a white noise error process. In lag operator form, equation (1) reduces as follows

$$y_t - \theta_1 y_{t-1} - \theta_2 y_{t-2} - \cdots - \theta_p y_{t-p} = \varepsilon_t \tag{2}$$

$$\theta(L) y_t = \varepsilon_t \tag{3}$$

for $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_p L^p$ is the characteristic polynomial for the AR(P) function.

2.2.2 Moving Average (MA) Models

For a time series y_t that has a moving average process of order q ie MA(q) is expressed as series of white noise processes $\sim N(0, \sigma_\varepsilon^2)$ as shown below

$$y_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} \tag{4}$$

The MA(q) is always stationary, as the observations are as a weighted moving average over past errors. In lag operator form, it's expressed as

$$y_t = \phi(L) \varepsilon_t \tag{5}$$

where the characteristic polynomial for the MA(q) is $\phi(L) = 1 + \phi_1 L + \phi_2 L^2 + \cdots + \phi_q L^q$

2.2.3 Autoregressive Moving Average (ARMA) Models

An ARMA is a combined process of both autoregressive process of order p and series of white noise process of order q, forming ARMA (p,q) expressed as

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} \tag{6}$$

Re-arranging equation (6)

$$y_t - \theta_1 y_{t-1} - \theta_2 y_{t-2} - \cdots - \theta_p y_{t-p} = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} \tag{7}$$

In lag operator form, equation (7) is expressed as

$$\theta(L) y_t = \phi(L) \varepsilon_t \tag{8}$$

where $\theta(L)$ and $\phi(L)$ are the characteristic polynomial for the AR(P) and MA(q) respectively as indicated above.

2.2.4 Autoregressive Integrated Moving Average (ARIMA) Models

Conversion of ARMA to ARIMA involves introduction of integration to ARMA process. The order of integration is the minimum number of differences required to obtain a stationary ARMA series. Since the moving average portion of the ARMA is always stationary, the autoregressive portion is always the cause for non-stationary. By making the autoregressive portion stationary by find the difference, equation (8) reduces to

$$\theta(L)(1-L)^d y_t = \phi(L)\varepsilon_t \tag{9}$$

where $(1-L)^d$ is the difference of order d. There are four special types of ARIMA

- ARIMA(0,0,0)- white noise process
- ARIMA (0,1,0)-Random walk process
- ARIMA(0,0,q)- Autoregressive process
- ARIMA(p,0,q)- autoregressive moving average

2.2.5 Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

The ARIMA (p,d,q) in equation (9) is considered as non-seasonal ARIMA as it does not contain seasonal terms. Adding additional seasonal term to the non-seasonal ARIMA result to ARIMA(p,d,q)$(P,D,Q)_m$. Where m is the number of observation per year and P,D,Q are seasonal period back shift of p,d,q respectively.

ARIMA(p,d,q)$(P,D,Q)_m$ is given as (Hyndman and Athanasopoulos, 2018)

$$\theta(L)\Theta(L)(1-L)^d(1-L^m)^D y_t = \phi(L)\Phi(L)\varepsilon_t \tag{10}$$

For $\Theta(L) = 1 - \Theta_1 L^m - \Theta_2 L^{2m} - \cdots - \Theta_{Pm} L^p$ and $\Phi(L) = 1 + \Phi_1 L^m + \Phi_2 L^{2m} + \cdots + \Phi_Q L^{Qm}$

2.2.6 The Box – Jenkins Technique

Box and Jenkins [22] introduced an three steps which are iterative to model and forecast using ARIMA models as follows;

- model identification

- Model estimation
- diagnostic checking steps (if the specification of a stationary univariate process fails, repeat the steps)
- forecast

(a) model identification

Model identification is the process of identifying the order of autoregressive process, integrated process and the moving average process corresponding to p,d,and q of ARIMA respectively.

To find a ARIMA model, it's a condition that the time series is stationary. A stationary times series is characterized by constant mean and variance. The mean and variance may be variant as a result of deterministic trend in a time series. To make a time series stationary, the integration process is performed, which is simply finding the difference of the time series. Within the model identification step, unit root test is performed to test for stationary and determine the integration order of a time series. This study applied ADF test (Dickey and Fuller, [23] and [24]) and P-P test (Phillips and Perron [25]). The model used in testing ADF test is as formulated in equation (11) while for P-P test is as defined in equation (12);

$$y_t = c + \delta t + \phi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t \tag{11}$$

$$y_t = c + \delta t + \phi y_{t-1} + \varepsilon_t \tag{12}$$

Both unit root test use similar test statistic defined as;

$$ADF_\tau = \frac{\hat{\phi} - 1}{SE(\hat{\phi})} \tag{13}$$

The null hypothesis for unit root tests states that there exist unit root ie $H_0 : \phi = 1$ against an alternative hypothesis of $\phi < 1$.

Both unit root test are in agreement that the decision is to fail to reject the null hypothesis in level as their p-values are greater than 0.05. In level, monthly domestic credit rate is non stationary. This indicates there exists a significant effect of external shocks on domestic credit. Over the sample period, domestic credit is heterogeneous and non constant mean. After the first difference, domestic credit attains stationary properties as the p-value is less than 0.05, thus reject

Table 1: Unit root test result

	ADF test		P-P Test	
	statistics	pvalue	statistics	pvalue
In level	-0.8464	0.9564	-1.6564	0.9769
Δ^1	-4.8469	0.01	-250.49	0.01

the null hypothesis of non-stationary. Monthly domestic credit is of integrated of order 1 ie I(1) thus the value of d in ARIMA(p,d,q) is 1.

Box and Jenkins proposed autocorrelation function (ACF) and partial autocorrelation function (PACF) to generate empirical autocorrelations pattern. The formula for ACF (ρ_h) and PACF ($\phi_{h,h}$) are given as in equation (14) and (15) respectively.

$$\rho_h = corr(y_t, y_{t-h}) = \frac{\gamma_h}{\gamma_0} \tag{14}$$

$$\phi_{h,h} = cov(y_t, y_{t+h} | y_{t+1}, y_{t+2}, \dots, y_{t+h-1}) \tag{15}$$

Where $h = 1, 2, 3, \dots, n-1$, $\gamma_h = cov(y_t, y_{t-h})$ and γ_0 is the covariance at lag zero. The behavior of ACF for AR(p) is gradual tall off while for MA(q) it cut off at lag q. On the other hand, PACF for AR(P) cuts off at lags q while for MA(q) there is a gradual tail off.

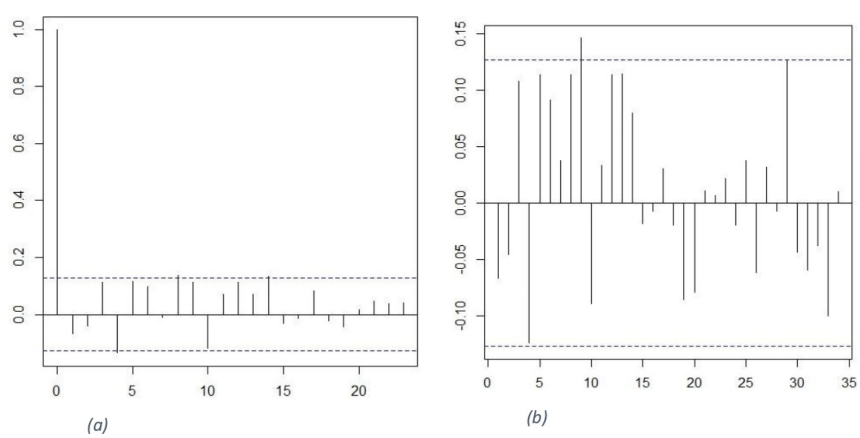

Figure 2: First difference ACF and PACF

From figure 2 (a), ACF tips off at lag 0 and there is a significant spike at lag 4. Similarly, PACF tips off at lag 0 with significant spike at lag 9 as shown in

Figure 2 (b). This is an indication of a seasonal component in domestic credit. The optimal model considering the ACF and PACF is ARIMA(0,1,0)$(1,0,0)_{12}$.

(b) Model estimation

Model estimation involves estimating the model parameter corresponding to the moving average process, the autoregressive process and the seasonal process, with the information score for the model included. The parameters are estimated maximizing the function (Hyndman and Athanasopoulos [26]);

$$L^*(Y_t|Y_{t-1},\delta_0) \tag{16}$$

where L^* is the conditional likelihood function without the constant terms and $\delta_0 = (\phi, \theta)$

Information criterion is a technique for selecting a model from a finite set of model. Akaike's information criterion (AIC) , corrected Akaike's information criterion (AIC_c) and Bayesian information criterion (BIC)are considered in this study. The better model fit is the one that has lower values of AIC and BIC. For any given model, the AIC is given as

$$AIC = -2logL(\hat{\theta}) + 2k \tag{17}$$

where $logL(\hat{\theta})$ is the maximized log-likelihood function with k parameter and t sample data points. Corrected AIC is given as;

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1} \tag{18}$$

Similarly, for any model the BIC is given as

$$BIC = -2logL(\hat{\theta}) + klog(t) \tag{19}$$

Three measure of accuracy are considered, namely; namely mean absolute error (MAE), root mean square error (RMSE) and mean average absolute error (MAPE) formulated as shown in equations (20), (21) and (22) respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{20}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}} \tag{21}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{e_i}{y_i}| \tag{22}$$

The auto.arima function in forecast package in R software, which returns the best ARIMA model according to AIC, AIC_c and BIC values based on stepwise algorithm, is used to return the best model. To model domestic credit, ARIMA(2,1,2)$(1,0,0)_{12}$ is the best fit. The parameter estimates are as shown in table 2. The estimated model has a white noise of 0.0132 standard deviation and a log-likelihood statistic of 697.43. From the measure of accuracy result, on average the fitted model is less than one percent off the observed values.

Table 2: ARIMA model estimation

			a			parameters
	ar1	ar2	ma1	ma2	sar1	drift
estimate	-1.2170	-0.8569	1.1378	0.7340	0.1603	0.0114
s.e	0.1189	0.0840	0.1572	0.1078	0.0683	0.0009
		b				Overall model
	σ^2	log likelihood	AIC	AICc	BIC	
	0.0002	698.43	-1382.86	-1382.37	-1358.52	
		c				Model accuracy
	RMSE	MAE	MAPE			
	0.0130	0.0007	0.0659			

(c) diagnostic test

ARIMA model residual analysis involves autocorrelation, heteroscedasticity and normality tests. Normality test uses Ljung-Box test statistics given as

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{r_k^2}{n-k} \tag{23}$$

where n is the sample size, r_k^2 is autocorrelation of sample at k lags and m is the lag order. Autocorrelation test is performed by residual ACF test while heteroscedasticity test is performed by standardized residual plot. The diagnostic test results are as shown in figure 4. The standardized residual plot shows homoscedasticity in the data set. Residual ACF shows no significant autocorrelation and the Ljung-Box test p-values are all well above 0.05 implying they are non significant.

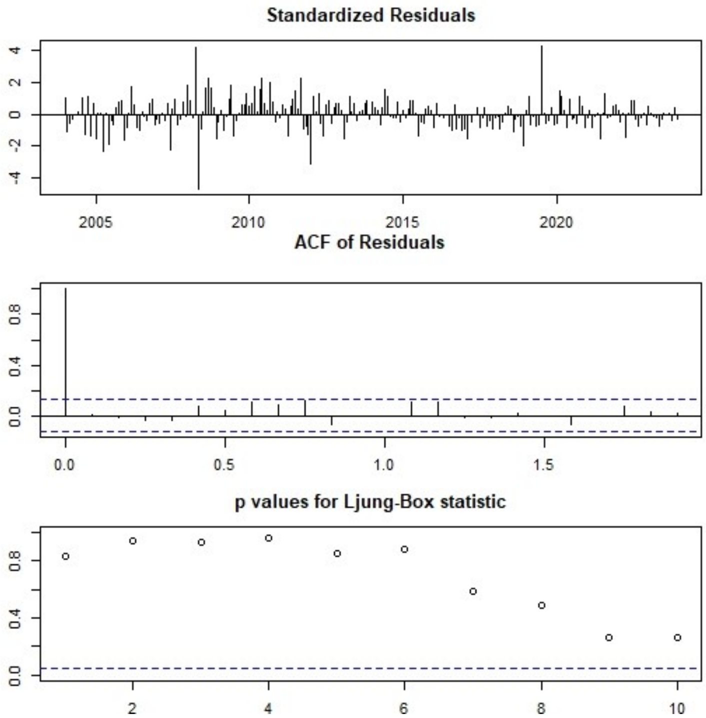

Figure 3: Model diagnostics

(d) Forecast

Considering an expanded ARIMA (p,1,q) of integrated order one (Brockwell and Davis [27])

$$(1-\theta_1 L-\theta_2 L^2-\cdots-\theta_p L^p)(1-L)y_t=(1+\phi_1 L+\phi_2 L^2+\cdots+\phi_q L^q)\varepsilon_t \quad (24)$$

expanding the left hand side of equation (24)

$$[1-(1+\theta_1)L+(\theta_1-\theta_2)L^2+\cdots+(\theta_{p-1}-\theta_p)L^p+\theta_p L^{p+1}]y_t=(1+\phi_1 L+\phi_2 L^2+\cdots+\phi_q L^q)\varepsilon_t \quad (25)$$

expanding both sides of equation (25)

$$y_t-(1+\theta_1)y_{t-1}+(\theta_1-\theta_2)y_{t-2}+\cdots+(\theta_{p-1}-\theta_p)y_{t-p}+\theta_p y_{t-p+1}=\varepsilon_t+\phi_1\varepsilon_{t-1}+\phi_2\varepsilon_{t-2}+\cdots+\phi_q\varepsilon_{t-q} \quad (26)$$

Making y_t the subject of the formula

$$y_t = (1+\theta_1)y_{t-1} - (\theta_1 - \theta_2)y_{t-2} - \cdots - (\theta_{p-1} - \theta_p)y_{t-p} - \theta_p y_{t-p+1} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \cdots + \phi_q \varepsilon_{t-q} \quad (27)$$

For $t = T+1$

$$y_{T+1} = (1+\theta_1)y_T - (\theta_1 - \theta_2)y_{T-1} - \cdots - (\theta_{p-1} - \theta_p)y_{T-p+1} - \theta_p y_{T-p+2} + \varepsilon_{T+1} + \phi_1 \varepsilon_T + \phi_2 \varepsilon_{T-1} + \cdots + \phi_q \varepsilon_{T-q+1} \quad (28)$$

Forecast to h step ahead is given as shown in equation (28)

$$y_{T+h|T} = (1+\theta_1)y_{T+h-1} - (\theta_1 - \theta_2)y_{T+h-2} - \cdots - (\theta_{p-1} - \theta_p)y_{T+h-p} - \theta_p y_{T+h-p+1} + \varepsilon_{T+h} + \phi_1 \varepsilon_{T+h-1} + \phi_2 \varepsilon_{T+h-2} + \cdots + \phi_q \varepsilon_{T+h-q} \quad (29)$$

For the error terms only the previous observed residual ε_{T+h-1} is included as all the other errors terms are replaced by zero, reducing equation (29) to

$$y_{T+h|T} = (1+\theta_1)y_{T+h-1} - (\theta_1 - \theta_2)y_{T+h-2} - \cdots - (\theta_{p-1} - \theta_p)y_{T+h-p} - \theta_p y_{T+h-p+1} + \phi_1 \varepsilon_{T+h-1} \quad (30)$$

Forecast values form January 2024 to December 2024 are as shown in table 3 and figure 4, with a 95% confidence interval. Domestic credit sector will experience a rise it credit value in the years 2024. The values will range from 7.117 to 8.039 Trillions by December 2024. The projected rate of increase will approximately more than 1 percent but less than 1.3 percent.

Table 3: Banks' domestic credit forecast results

Time	domestic credit	95% lower bound	95% upper bound	Δ %
Jan 2024	7117196	6935394	7303764	1.217
Feb 2024	7203431	6954456	7461320	1.212
Mar 2024	7279820	6979666	7592881	1.060
Apr 2024	7356737	7002531	7728860	1.057
May 2024	7433621	7039242	7850095	1.045
Jun 2024	7512585	7077989	7973866	1.062
Jul 2024	7604214	7127893	8112365	1.210
Aug 2024	7689815	7179454	8236456	1.126
Sep 2024	7774258	7227137	8362799	1.099
Oct 2024	7859166	7276852	8488079	1.092
Nov 2024	7955806	7340911	8622206	1.230
Dec 2024	8039222	7389962	8745525	1.048

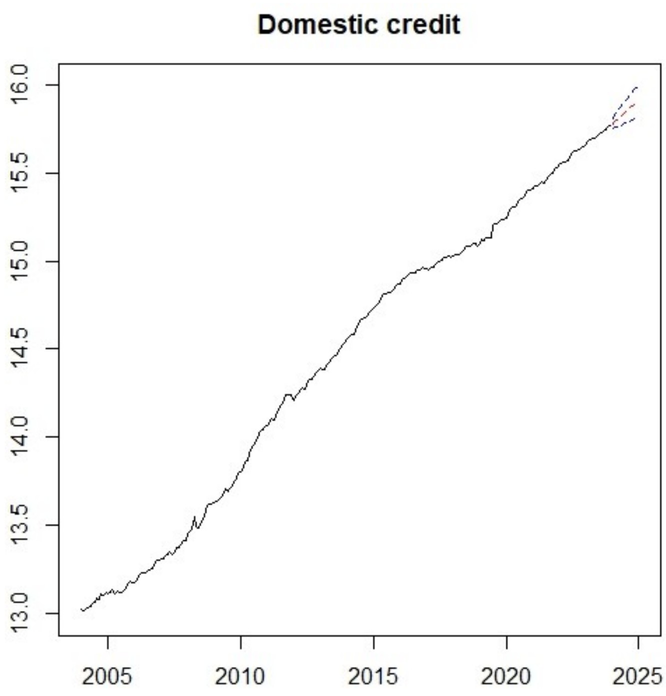

Figure 4: Domestic credit forecast

3 Discussion and conclusion

The objective of the study was analyze domestic credit growth, its times series property and its expected value and trend.Generally, there has been a continuous increase in domestic credit from the period 2004 to 2023. Box-Jenkins framework was used to estimate the ARIMA model. In the first step, Unit root test and correlogram analysis were conducted. Domestic credit is non stationary in level though its of integration order one ie I(1). Both ACF and PACF tips off at lag 0 implying p and q parameters equal to zero. There are significant spikes in ACF and PACF at 4 and 9 respectively. This suggest the presence of seasonality component in the ARIMA model. In the second step, ARIMA(2,1,2)$(1,0,0)_{1}2$ is estimated as the best fit for the sample period. The model has a high level of error accuracy as fitted values are less than percent of the observed values. In the model diagnostic step, all assumption of ARIMA analysis are meet' there is no hetetroscedasticity, no significant auto-correlation and insignificant Ljung-Box test p-values. The estimated model is used to forecast monthly value over a forecast horizon of twelve period.
From the study,domestic credit has a varying constant and mean. Thus, its highly influenced by economic shocks that it experiences at any given time. Considering the sample period, ARIMA model with p,d,q parameter corresponding to 2,1,2 and seasonal parameter 1,0,0 for P,D,Q respectively is the best for modeling and forecasting. Its projected that domestic credit will continue to rise in the year 20024 through to December. The expected domestic credit value in December 2024 is 8.039 Trillions with a confidence interval from 7.389 to 8.746 Trillions. Kenya government should put in place monetary policy that favors bank credit growth and competition in the banking sector.

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