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MODELING THE CONTRIBUTION OF THE MANUFACTURING SECTOR TO THE GROSS DOMESTIC PRODUCT OF KENYA USING TIME SERIES ANALYSIS

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Abstract: The manufacturing sector is considered a pivotal contributor to the growth of the economy around the globe. Kenya relies on the manufacturing sector to generate revenue and ultimately enhance the growth of the economy. Despite the key purpose played by these sectors in the economy, inflation rate has diversely affected their performance. The purpose of the study was to develop the Autoregressive Integrated Moving Average time series model to forecast the inflation rate in Kenya. The analysis utilized secondary data from the Kenya National Bureau of Statistics and the model was fitted to the data using R. The ARIMA(0,1,1)(0,0,2)[12] with the information criterion of 576.24 was identified as the best model. Based on the forecasting, it was established that there will be a slight shift in the inflation in the coming years. Therefore, the government should use wage and price control to fight inflation but put in place policies to prevent recession and job loss in the country. The government should also employ contractionary monetary policy to fight inflation by reducing the money supply in the economy through decreases bond prices and increased interest rates. Implementation of these recommendations might assist in reducing the rate of inflation in the country.

1. INTRODUCTION

For any economy developing long-term economic frameworks, a strong manufacturing foundation is proving to be a reliable factor. Most of the developed economies around the globe attribute their success to their functional manufacturing sector (Yong, 2018). Countries that are achieving rapid industrialization are notably initiating deliberate policies that promote value addition and diversification in the manufacturing sector. The manufacturing sector in Africa is facing transformation to reflect changes in national policies, dynamic domestic demand, and the world market variances (Undesa, 2020). The essence of the manufacturing sector to the economies of the African countries varies across different periods since independence; notwithstanding, the shift to emphasize the contribution of the sector to the national income has increased in recent years. Regardless of manufacturing being considered a small sector in African countries, that is with regard to total output share and employment capacity, growth of the sector is proving to be a crucial contributor to economic development (Oketch, 2014; Yang et al., 2021). According to (KAM, 2021; Republic of Kenya, 2018), for Kenya to achieve the intended GDP growth of up to 25% by 2025, urgent and strategic steps are needed in order to achieve the goal. In accordance with Vision 2030 and the recent Big 4 Agenda, the Government is demonstrating interests to revitalize the manufacturing sector. In 2018, the government of Kenya declared the manufacturing sector as a prioritized area to invest for the country to experience economic growth. KAM (2021), suggests that, for Kenya to achieve economic growth, the government ought to initiate policies that provide a conducive environment to allow the manufacturing sector to thrive. Some of the areas that need to be addressed by the government include but are not limited to injecting more money into the economy, improving the transport sector, and addressing the issue of multiple levies and charges by counties.

Manufacturing is the only pillar in the Big Four Agenda which guarantees to create jobs and improve its GDP contribution in the short to medium term but the government is still struggling to create a conducive environment for the manufacturing sector. At present, Kenyan manufacturers are at a cost disadvantage of up to 12% on the majority of goods they manufacturer compared to foreign companies (Mwangi, 2019). As such, manufacturing firms choose to relocate or restructure their processes by importing low-cost products from countries such as South Africa, India, and Egypt which leads to unemployment (Karanja & Kennedy, 2016). This scenario implies that manufacturing companies are facing performance difficulties which are reflected on the declining contribution of the manufacturing sector to GDP from 11.8% in 2011 to 8.4% as of 2017. Majority of the companies- citing challenges in the operating environment as the pertinent issue (KAM, 2019). According to Oketch (2014), most manufacturing companies in Kenya are operating at a technical efficiency of 59% and average at 74% which provokes doubts whether it will be possible to achieve Vision 2030. Considering the discussion, there is a need to conduct a time series analysis that can forecast performance of the manufacturing industry. A forecast can help the country to better plan its resources with regard to inputs/policies needed for the manufacturing industry to perform better.

This study will therefore establish a univariate time series model to forecast inflation rates affecting performance of the manufacturing sector in Kenya. The Government of Kenya has been taking measures to address the issues of cost of production, cost of energy, increasing the amount of money in circulation, and improving the transport system in a bid to improve the performance of the manufacturing sector. In 2019, the Treasury announced that the government has developed a framework that allows a deduction of 30% of the total electricity bills by manufacturers in a bid to reduce to reduce the cost of electricity. Additionally, the government allocated a sum of KES 1.1 billion for the revitalization of the textile and leather industry. Also, the government injected KES 1.7 billion into the SME sector and an extra KES 1 billion to modernize the Kenya Industrial Research and Development Institute. The treasury also insisted on a slogan that 'Buy Kenya Build Kenya', which seeks to ensure local public and private entities promote local industries, for instance, ministries purchasing motor vehicles from companies that have local assembly plants (Ministry of Finance, 2019). Essentially, the study is important in forecasting the inflation rate that affect manufacturing sector. The forecast enables the necessary stakeholders to invest the right resources in the industry in a bid to handle inflation that affect the performance of the sector to the country's GDP.

The study focused on forecasting the inflation rate that greatly affects manufacturing sector in Kenya using the ARIMA (Autoregressive Integrated Moving

Average) time series model. The data considered covered a period between 2005 and 2019 on a quarterly basis. Karpak & Topcu (2010), illustrates that regulations and policies influence the success of SMEs in their research. The study was conducted in Turkey when the two scholars recommended the government to review regulations in the order to provide a better environment for the manufacturing enterprises. The research considers a few factors influencing the success of the SMEs and the dependencies among the factors. The factors considered include but not limited to ICT, facility location, ability to export, process technology, sales (revenues), and access to credit, and availability of capital. The study utilized the concept of Analytical Network Process (ANP) which consists of networks that contain factors of the problem under consideration. Considering the limit matrix priorities, regulations and policy turned out to be the most influential factor to the success of the manufacturing industry with 17.36%. Facility location influenced the success of SMEs by 11.57% while intensity of competition had 9.79% influence. (Oláh et al., 2019), used a decision tree to study how financial and ICTs variables affected global manufacturing performance. From the research, it is clear that financial variables are better predictors of reduced or improved performance of the manufacturing industry when compared to the ICTs. The observation is consistent with the report by (Kiprotich et al., 2018; Otieno, 2015), which posited that performance is induced by competitive and strategic factors. The research reaffirms that inadequate access to finance contributes to weak industrial performance. The paper also concludes that industries that record low equity finances or stock sales register improved sales growth and hence different sources of funding informs different industry performance. Also, ICTs do not improve the performance of industries as shown in regional comparisons. The research proved that while there is low technology sophistication in Africa and East Asia, still the regions record strong industry performance. For that reason, it is better to compare the effect of ICTs across different regions with different level of technology. Therefore, the paper concludes that different levels of technology per region influences the performance of the manufacturing industry. In addition, financial support to the manufacturing industry is more significant compared to ICTs especially in the developing countries.

The conclusion has a two-way effect given that, established manufacturing companies will consider the state of road transport infrastructure before setting up new firms. The conclusion is true for countries whose manufacturing industries rely on road transport to deliver goods. Adelheid arrived at the conclusion by utilizing micro-level data which revealed that utilizing distance linearly results to estimates that prove that moving 10km away from motorways connecting regions reduces the number of new plants by 0.9% to 3.8%. Quadratic approximations show the impact new motorways are larger and fade away by 0.1% to 0.5% for every 10km. However, the polynomial approximations can only explain the discrete distance effects and not the complicated nonlinearities. In addition, the research proves that a proper comprehension of a large and better transport system will influence the set of new manufacturing firms. Given that inflation-growth linkage has been a topic of academic discourse in several research, Judith & Chijindu (2016), chose to investigate the impact of inflation and growth on the performance of certain sectors of the Nigerian economy and the focus was on the manufacturing sector. They utilized the annual time series data back to 1982 up to 2014 which resulted in the conclusion that interest rate and inflation have non-significant and negative impact on the manufacturing sector respectively.

Therefore, this study seeks to apply the ARIMA time series model to forecast the inflation rate in Kenya. The forecast is done for a period of 3 years from the year 2022 to

2025 after fitting an appropriate model to the data. The information obtained from this study will help in creating a favorable environment for the manufacturing sector to thrive.

2. MATERIAL AND METHOD

2.1 Data Collection and Analysis

The study utilized secondary data which was collected from the Kenya National Bureau of Statistics (KNBS). The data is freely available at https://www.knbs.or.ke/. The study considered data from the period of 2005 to 2021 on a monthly basis. The information criterion was used for model selection such that the model with the least information criterion was considered the best model. The inflation dataset was analysed using time series modeling algorithm in R software (Team, 2021).

2.2 Autoregressive Integrated Moving Average Model

ARIMA uses three tools for modelling the relationship between observations of the same variable over a sequential time interval. The model was popularized by Box and Jenkins for time series forecasting (Box et al., 1970; D. Montgomery et al., 2008). The model is denoted by ARIMA(p, d, q) whereby p represents the order of the Autoregressive (AR) terms, d is the number of times the series has to be differenced to achieve stationarity, and q denotes the order of Moving Average (MA) terms. The ARIMA model considers past data and reduces it into an AR process which is a recollection of past observations into an integrated process that justifies stationarity. The MA utilizes lagged entries of the forecast errors of previous observations to improve present forecast.

The Autoregressive Moving Average process is denoted by ARMA (*p*, *q)*, the mentioned model is a merger of the simple MA(*q)* and AR*(p)* models (Kinyili & Wanyonyi, 2021). The following is a representation of the ARMA (*p*, *q*) model:

$$X_t = \beta_1\epsilon_{t-1} + \beta_2\epsilon_{t-2} + \cdots + \beta_q\epsilon_{t-q} + \alpha_1X_{t-1} + \alpha_2X_{t-2} + \alpha_3X_{t-3} + \cdots + \alpha_pX_{t-p} + \epsilon_t \tag{1}$$

Where $\beta_1\epsilon_{t-1} + \beta_2\epsilon_{t-2} + \cdots + \beta_q\epsilon_{t-q}$ is the MA(q) and $\alpha_1X_{t-1} + \alpha_2X_{t-2} + \alpha_3X_{t-3} + \cdots + \alpha_pX_{t-p}$ is the AR (p). The integrated ARMA model is a broad class of ARMA model (Kinyili & Wanyonyi, 2021; Wanyonyi et al., 2021). It is referred to as integrated because of the differencing factor needed to alleviate the non-stationary component and achieve stationarity in the model.

The series is differenced to achieved stationarity (Mathenge, 2019). The first difference of the manufacturing sector resulted to ARIMA$(p, 1, q)$

$$Inms_t = \mu_0 + \alpha_1Inms_{t-1} + \alpha_2Inms_{t-2} + \cdots + \alpha_pInms_{t-p} + \epsilon_t + \beta_1\epsilon_{t-1} + \cdots + \beta_q\epsilon_{t-q} \tag{2}$$

$Inms_t$ represents the manufacturing sector performance rates that are differenced once andμ, $\alpha$and β are the estimated parameters.

2.3 Box-Jenkins Methodology

Box and Jenkins proposed the following methodology in time series modeling; model identification, parameter estimation, model parsimony and forecasting (Box et al., 1970; Montgomery et al., 2008).

Model Identification

The study attempted to identify the appropriate model structure either, AR, MA or ARIMA. The identification was achieved by observing plots of the initial data that was essential in determining the need for differencing. If the data happens to be non-stationary, then the study conducted a first order differential to achieve stationarity. Differencing can be iterated until stationarity is achieved with the number of iterations being recorded as d, then it was denoted as ARIMA(p, d, q). An Augmented Dickey Fuller (ADF) test was conducted to examine the stationarity of the data by investigating the absence or existence of a unit root.

Parameter Estimation

The Yule Walker equations was used to estimate parameters in ARMA although the approach has since proved to exhibit bias since the method of moments results in inconsistency in parameter estimation. Maximum likelihood estimation as a robust method has been proved to overcome the aforementioned challenges as mentioned by Brockwell & Davis (2002). The Gaussian time series X_t has a covariance matrix denoted as $\Gamma_n = E(X_n X_n^{'})$ where$n = 1,2,\cdots,n$. Assuming that Γ_n is a non-linear singular matrix, the likelihood of X_n is given by:

$$L(\Gamma_n) = (2\pi)^{-\frac{n}{2}}(det\Gamma_n)^{-\frac{1}{2}}\exp\left(-\frac{1}{2X_n^{'}\Gamma_n^{-1}X_n}\right) \tag{3}$$

We then express Γ_n in terms of finite numbers of unknown parameters $\phi_q, \theta_p, \sigma^2$ that is $\Gamma_n = \phi_q, \theta_p, \sigma^2$. A maximum likelihood estimator maximizes the likelihood function $L(\Gamma_n)$ for a selected data set. Given $X_1, X_2, \cdots, X_n$ are identically and independently distributed and n tends to be large enough, then the maximum likelihood estimators have a normal distribution with variances that are small as the case of asymptomatic normally distributed estimators (Brockwell & Davis, 2002). As a result, $X_t$will not be Gaussian in which case the maximum likelihood estimators become the best estimators. The ARMA models' parameters are numerically calculated by minimizing $\frac{\partial}{\partial\sigma^2}log(L(\Gamma_n)) = \frac{\partial}{\partial\sigma^2}logL(\phi_q, \theta_p, \sigma^2)$ where $\theta_p$and$\phi_q$represent MA and AR coefficients. The initial values of $\theta$and ϕ are fitted from the data as the computer program eventually systematically search for the values in the reduced log-likelihood function which yields least square estimates. Completion of the iterations, the variance is then computed by MLE.

Model Parsimony

The best model has a lower information criterion and the least parameters (Kinyili & Wanyonyi, 2021; Wanyonyi et al., 2021). The study will use a stepwise selection criterion utilizing Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and Akaike Information Criterion correction (AICc) to select the parsimonious model. Letting $Lmax$ be the maximum likelihood, $k$be the number of parameters and $n$be the sample size then

$$BIC = -2\ln L\,max + k\ln n \tag{4}$$

Due to their consistent estimates, Bayesian estimates are considered but their difficulty in handling complex models wherebу$n < \kappa$ makes the model unsuitable. As such, we may be forced to consider Akaike information criterion (AIC) (Antonov, 2016)

$$AIC = 2k - 2\ln L\,max \tag{5}$$

Corrections for the additional parameters are necessary based on asymptomatic property. The correction will result in the corrected akaike information criterion (AICc).

$$AIC_c = AIC + 2k(k+1)/(n-k-1) \tag{6}$$

AICc realigns the model parameters resulting in a more parsimonious model (Antonov, 2016). When considering a large sample size, the AICc converges to AIC and as such, the AIC is the preferred criterion by a majority of scholars (Barr et al., 2021; Dramani & Frimpong, 2020; D. C. Montgomery et al., 2015).

Forecasting

As a prerequisite of the Box-Jenkins approach, the model in use when explaining the time series and forecasting has to be stationary and invertible (Lidiema, 2017; Dritsakis & Klazoglou, 2019). Once the conditions have been achieved through steps such as differencing, the study can proceed to forecast future values. To confirm the accuracy of the ARIMA model, statistical computations of Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) were carried out.

3. RESULTS AND DISCUSSION

3.1 Time Series Plot

The data was transformed into time series data and a time plot was plotted. Figure 1 shows the time plot obtained to check existence of seasonal variation**.**

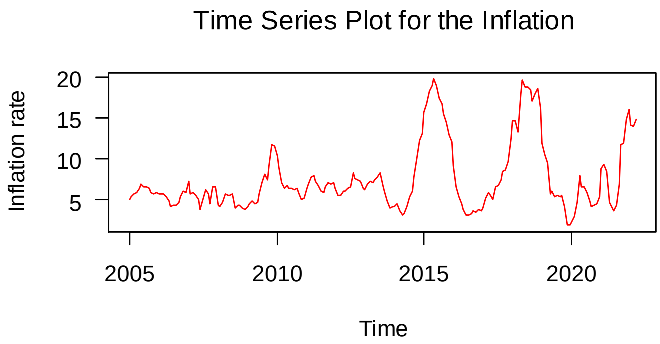

Figure 1. Time Series Plot for the Inflation Rate

The plot shows a cyclic effect. After every year the inflation rises and falls at the beginning of the following year, then rises again but the seasonal components remain constant. There is no outlier in the data which can lead to misappropriate results. Therefore, a curvature trend can easily be seen from the behavior of the plot.

3.2 Decomposition into Time Series Components

The time series was then decomposed into several components that include random or irregular movements, trend, seasonal variation and cyclic variation. The decomposed time components are as shown in Figure 2.

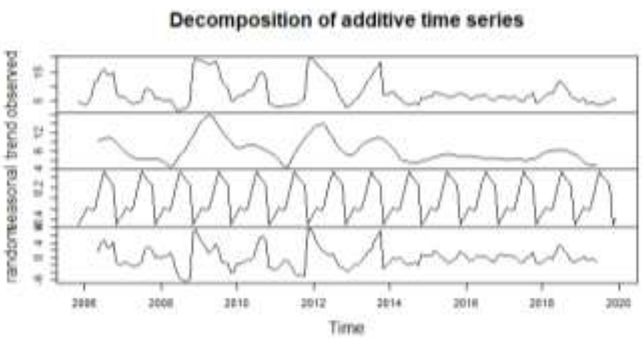

Figure 2. Seasonal Components

It can be seen from Figure 2 that the graph of seasonal and trend have some pattern even the randomness shows high variance in the early years.

3.3 Determination of the Stationarity of KNBS Data

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of inflation time series were also obtained. Figure 3 shows PACF and ACF for checking stationarity of the inflation time series.

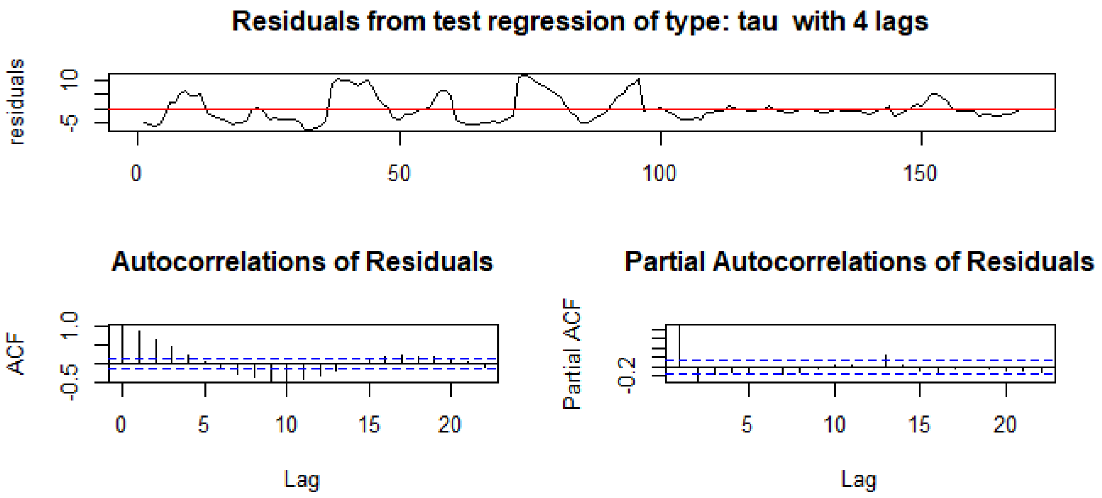

Figure 3. Autocorrelations and Partial Autocorrelations

The inflation time series shows a non-stationary behavior as shown by ACF and PACF together with the unit root in Figure 3. In order to ensure stationarity, differencing was done to the time series. The results of the differencing are shown in Figure 3.

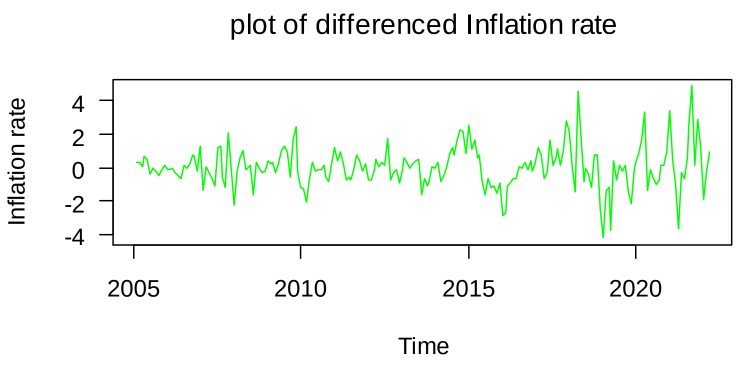

Figure 4. First Order Difference Time Series

The time series now shown some stationarity after first differencing as shown in Figure 4. The graph shows constant mean depicting a stationary time series.

The ACF of the stationary time series was then plotted. Figure 5 shows the ACF of the stationary time series.

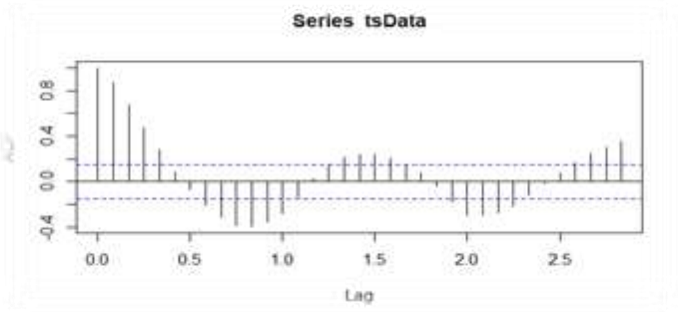

Figure 4. Auto Covariance Function of Differenced Time Series

The ACF decreases as the number of lag increases. This shows existence of seasonal effects and there is no linear association between observations separated by larger lags

In order to remove the seasonality component from the series and make the time series completely non-seasonal and stationary, the seasonal component was subtracted from the original series and final difference made it stationary.

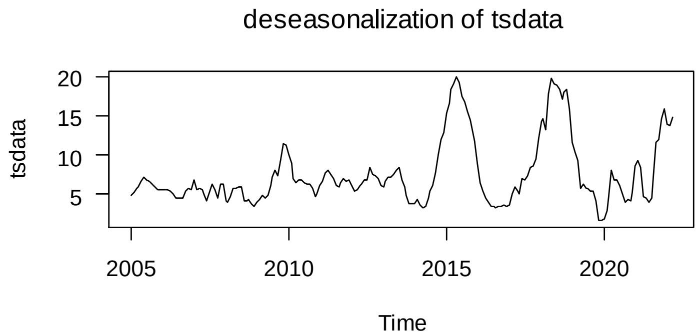

Figure 6. Time Series Without Seasonality

Figure 6 shows the time series seasonal components which were removed from the original time series data. Figure 7 shows the differenced deseasonalized series. This implies that both the seasonal and deseasonalized series are differenced once to achieve the stationarity.

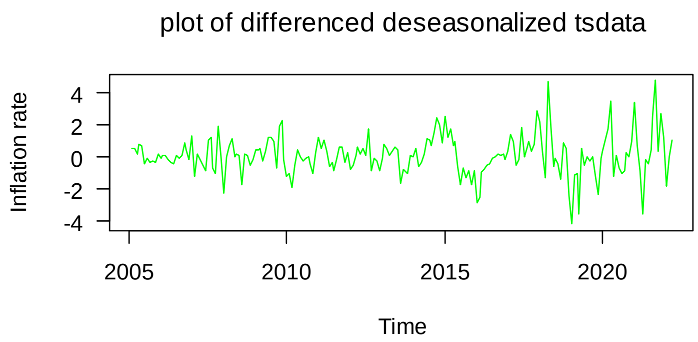

Figure 7. Differenced Deseasonalized Series

3.4 ARIMA model

The best ARIMA models were obtained by varying the values of p, d and q, and those with the least AIC were picked to be ARIMA (0,1,1)(0,0,2)[12] with AIC value of 576.24. The significance of the coefficients was checked using the p-values. Table 1 shows the regression coefficients and their corresponding standard errors and p-values corresponding to their z statistics.

Table 1. Regression Coefficients

Coefficients	Estimate	Std. Error	z value	p-value
ma1	0.32	0.06	5.27	0.00
sma1	-0.71	0.08	-9.14	0.00
sma2	0.14	0.08	1.66	0.03

From Table 1, both the effect of ma1, sma1 and sma2 are statistically significant since their p-values are less than alpha (0.05).

For a perfect ARIMA model, the residuals should have the following properties; they should be uncorrelated, if the correlations exist between residuals, then there is information left in the residual which should be used in computing forecasts. The residuals should also have zero mean to avoid the biasedness in the forecast. Figure 8 shows ACF of the residuals, the lack of correlation on the ACF plot shows that forecast model is good.

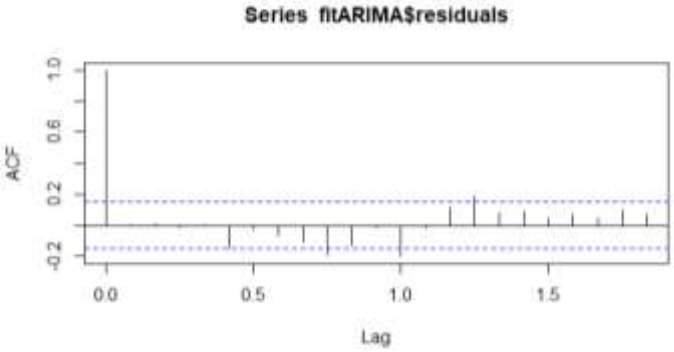

Figure 8. ACF of the Fitted Model

The residual should have a constant variance and should be normally distributed. These properties were checked using L-jung Box test and the normal Q-Q plot as shown below in Figures 9 and Figure 10.

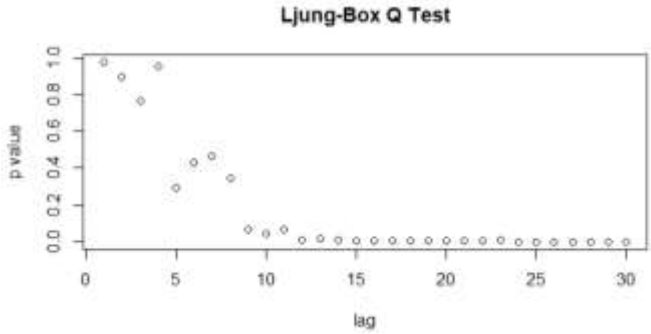

Figure 9. L-Jung Box Test

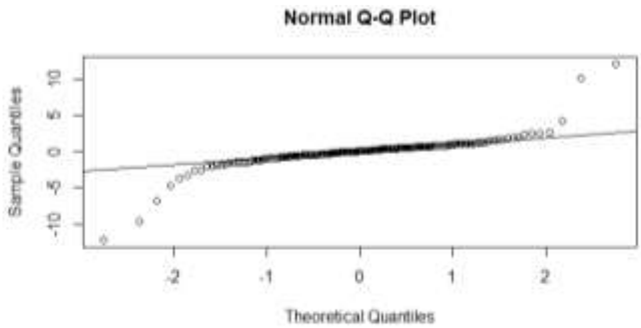

Figure 10. QQ and Normal Plot of ARIMA Residuals

Figure 9 shows the results of the Ljung-Box test statistics. Higher p-value (p-value=0.5105) show that autocorrelations do not come from white noise series. The residuals have constant mean and variance, and are normally distributed as shown in the normal Q-Q plot in Figure 10. Since the conditions were satisfied, the prediction was carried out.

3.5 Prediction of Inflation rates

The inflation rates for the next 3 years were estimated using the best selected ARIMA model. The estimation was done at a 99.5% level of significance. The forecast was then plotted as shows in Figure 11. The time series prediction plot shows that there will be a slight rise in the inflation rate from April 2022 to July 2022, then there will be a slight drop between September 2022 and August 2023 and finally maintains a constant rate.

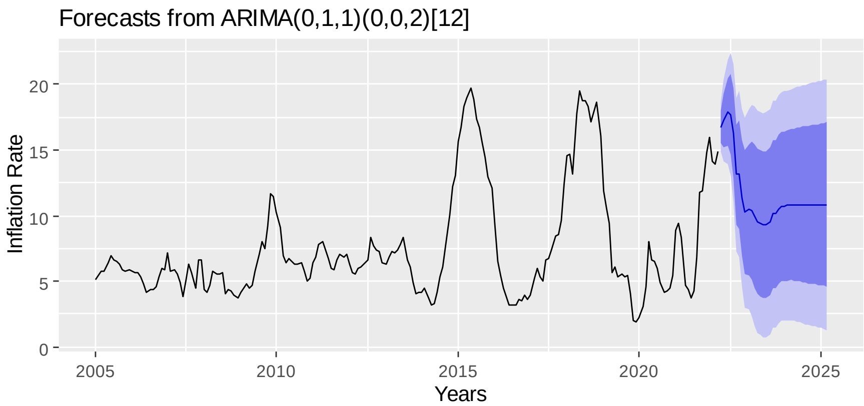

Figure 11. Forecast Plot

4. CONCLUSION

The study successful developed a model to predict future fluctuations in the inflation rates. It established that the country should expect a slight shift in the present inflation rates in three years to come. Therefore, the suggestions from this research and other actions should be taken as early as now to reduce inflation rates in the country. This will enable manufacturing industries to thrive well and continue contributing significantly towards the betterment of the Kenyan economy. Based on the findings, the following actions need to be considered. The government should use wage and price control to fight inflation but put in place policies to prevent recession and job loss in the country. The government should employ contractionary monetary policy to fight inflation by reducing the money supply in the economy through decreases bond prices and increased interest rates. Implementation of the recommendations might assist in reducing the rate of inflation in the country. This will create favorable environment for manufacturing sector to thrive and continue contributing significantly to the growth of the national economy at large.

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