Where is Kenya being headed to? Empirical evidence from the Box-Jenkins ARIMA approach

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Abstract

Using annual time series data on GDP per capita in Kenya from 1960 to 2017, the study analyzes GDP per capita using the Box – Jenkins ARIMA technique. The diagnostic tests such as the ADF tests show that Kenyan GDP per capita data is I (2). Based on the AIC, the study presents the ARIMA (3, 2, 1) model. The diagnostic tests further show that the presented parsimonious model is stable and reliable. The results of the study indicate that living standards in Kenya will improve over the next decade, as long as the prudent macroeconomic management continues in Kenya. Indeed, Kenya's economy is growing. The study offers 3 policy prescriptions in an effort to help policy makers in Kenya on how to promote and maintain the much needed growth.

Key Words: GDP per capita, Forecasting, Kenya

JEL Codes: C53, E37, O47

INTRODUCTION

Policy makers and analysts are continually assessing the state of the economy (Barhoumi *et al*, 2011). The Gross Domestic Product (GDP) is one of the primary indicators used to measure the healthiness of a country's economy (Onuoha *et al*, 2015). GDP is the broadcast measure of the total output of the economy (Ruffin, 1998). GDP is also used to determine the standard of living of individuals in an economy (Onuoha, *et al*, 2015) and is also a popular measure of economic growth. Economic growth can be defined as a sustained increase in per capita national output or net national product over a long period of time. Economic growth can also be seen as the quantitative increase in the monetary value of goods and services produced in an economy within a given year (Nyoni & Bonga, 2018a). Sustainable economic growth mainly depends on a nation's ability to invest and make efficient and productive use of the resources at its disposal (Nyoni & Bonga, 2017f).

In Kenya, just like in any other country, the need for a more consistent and accurate GDP forecast for the conduct of forward-looking monetary policy is unstoppable. This could be attributed to the fact that the availability of real-time data is very important especially in determining the initial conditions of economic activity on latent variables such as the output gap to make more realistic policy recommendations. This research attempts to model and forecast Kenyan GDP per capita over the period 1960 – 2017. The rest of the paper is organized as follows: literature review, materials & methods, results & discussion and conclusion; in chronological order.

LITERATURE REVIEW

Using an econometric Artificial Neural Network (ANN) model, Junoh (2004), predicted GDP growth in Malaysia using data ranging over the period 1995 – 2000 and found out that the neural network technique has an increased potential to predict GDP growth based on knowledge-based economy indicators compared to the traditional econometric approach. Lu (2009), in the case of China; modeled and forecasted GDP based on ARIMA models using annual data from 1962 to 2008 and established that the ARIMA (4, 1, 0) model was the optimal model. Bipasha & Bani (2012) forecasted GDP growth rates of India based on ARIMA models using annual data from 1959 to 2011 and found out that the ARIMA (1, 2, 2) model was the optimal model to forecast GDP growth in India. Dritsaki (2015) analyzed real GDP in Greece basing on the Box-Jenkins ARIMA approach during the period 1980 – 2013 and found out that the ARIMA (1, 1, 1) model was the optimal model. Wabomba *et al* (2016), in a Kenyan study, modeled and forecasted GDP using ARIMA models with an annual data set ranging from 1960 to 2012 and established that the ARIMA (2, 2, 2) model was the best for modeling the Kenyan GDP.

MATERIALS & METHODS

ARIMA Models

ARIMA models are often considered as delivering more accurate forecasts then econometric techniques (Song *et al*, 2003b). ARIMA models outperform multivariate models in forecasting performance (du Preez & Witt, 2003). Overall performance of ARIMA models is superior to that of the naïve models and smoothing techniques (Goh & Law, 2002). ARIMA models were developed by Box and Jenkins in the 1970s and their approach of identification, estimation and diagnostics is based on the principle of parsimony (Asteriou & Hall, 2007). The general form of the ARIMA (p, d, q) can be represented by a backward shift operator as:

$$\emptyset(B)(1-B)^d GDP_t = \theta(B)\mu_t \ldots\ldots\ldots\ldots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\emptyset(B) = \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) \ldots\ldots\ldots\ldots [2]$$

$$\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right) \ldots\ldots\ldots\ldots [3]$$

and

$$(1-B)^d GDP_t = \Delta^d GDP_t \ldots\ldots\ldots\ldots [4]$$

Where $\emptyset$ is the parameter estimate of the autoregressive component, θ is the parameter estimate of the moving average component, Δ is the difference operator, d is the difference, B is the backshift operator and μ_t is the disturbance term.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

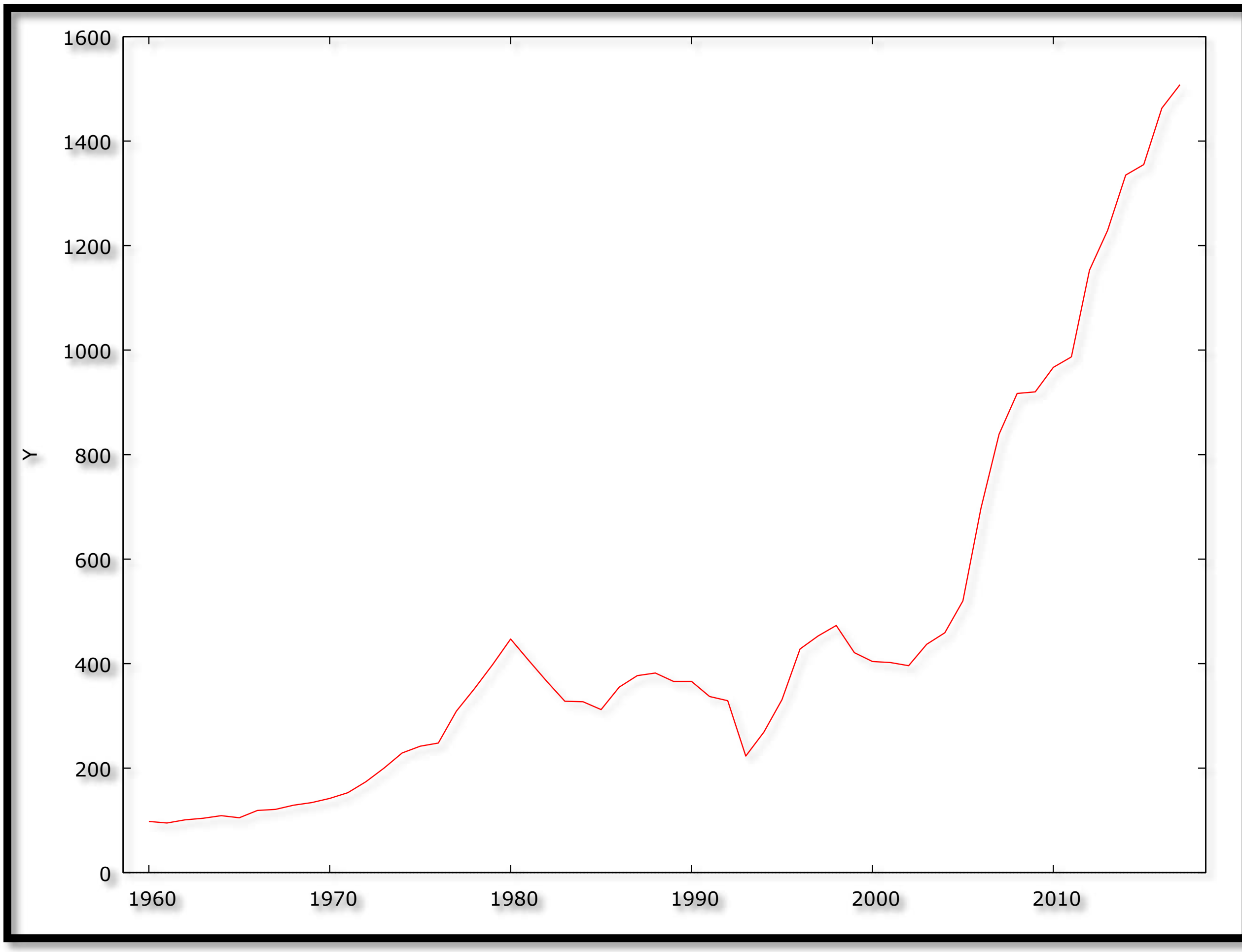
Data Collection

This paper is based on 58 observations (1960 – 2017) of annual GDP per capita (Y, referred to as GDP in the mathematical formulations above) in Kenya. The data used in this paper was collected from the World Bank online database, one of the most credible sources of macroeconomic data.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

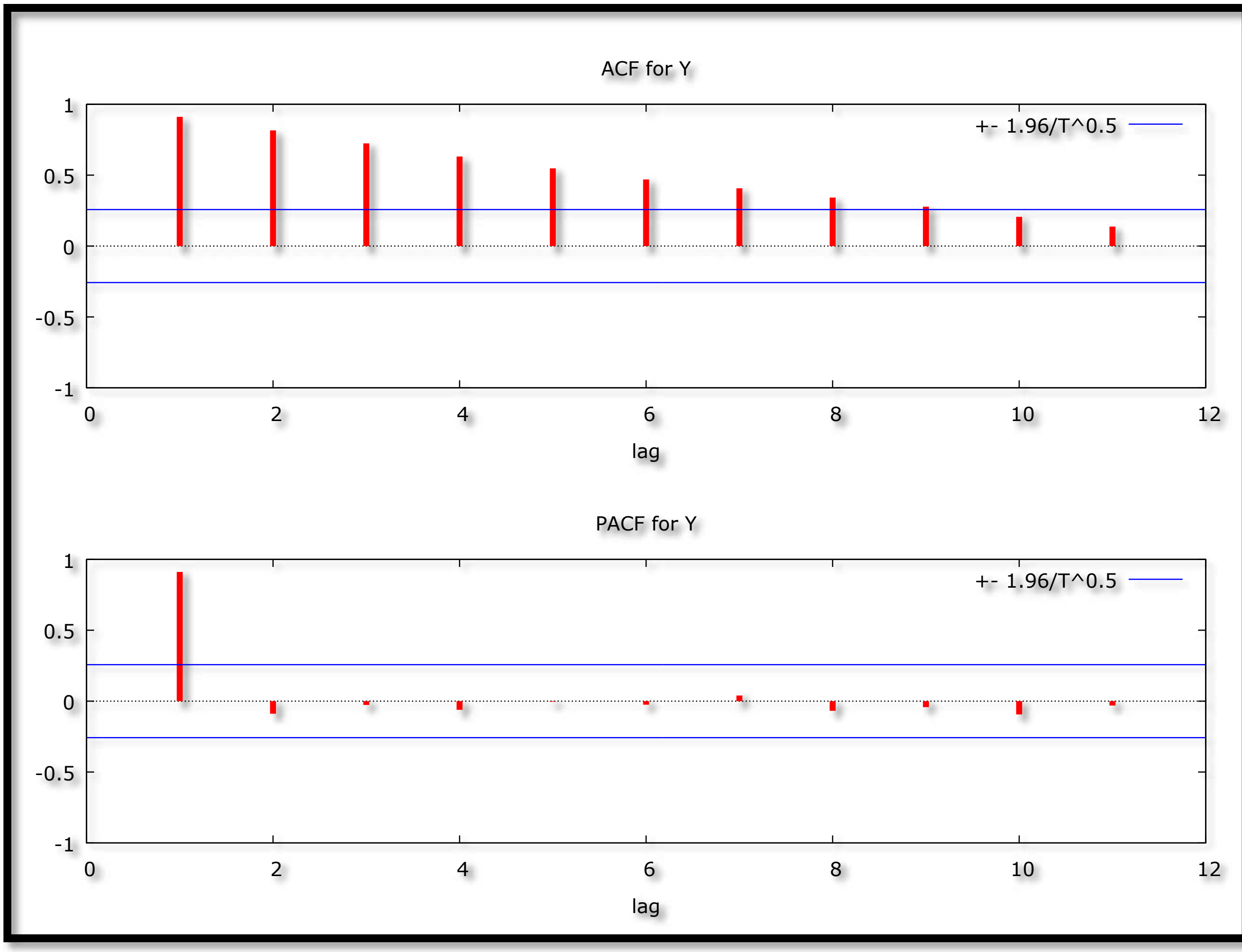
Figure 1



Y variable is not stationary because it is trending upwards over the period under study and this simply shows that the mean of Y is changing over time and thus its varience is not constant over time.

The Correlogram in Levels

Figure 2



The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	2.686539	1.0000	-3.557472	@1%	Not stationary
			-2.916566	@5%	Not stationary
			-2.596116	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	1.021526	0.9999	-4.137279	@1%	Not stationary
			-3.495295	@5%	Not stationary
			-3.176618	@10%	Not stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	3.547690	0.9998	-2.608490	@1%	Not stationary
			-1.946996	@5%	Not stationary
			-1.612934	@10%	Not stationary

The Correlogram (at 1st Differences)

Figure 3

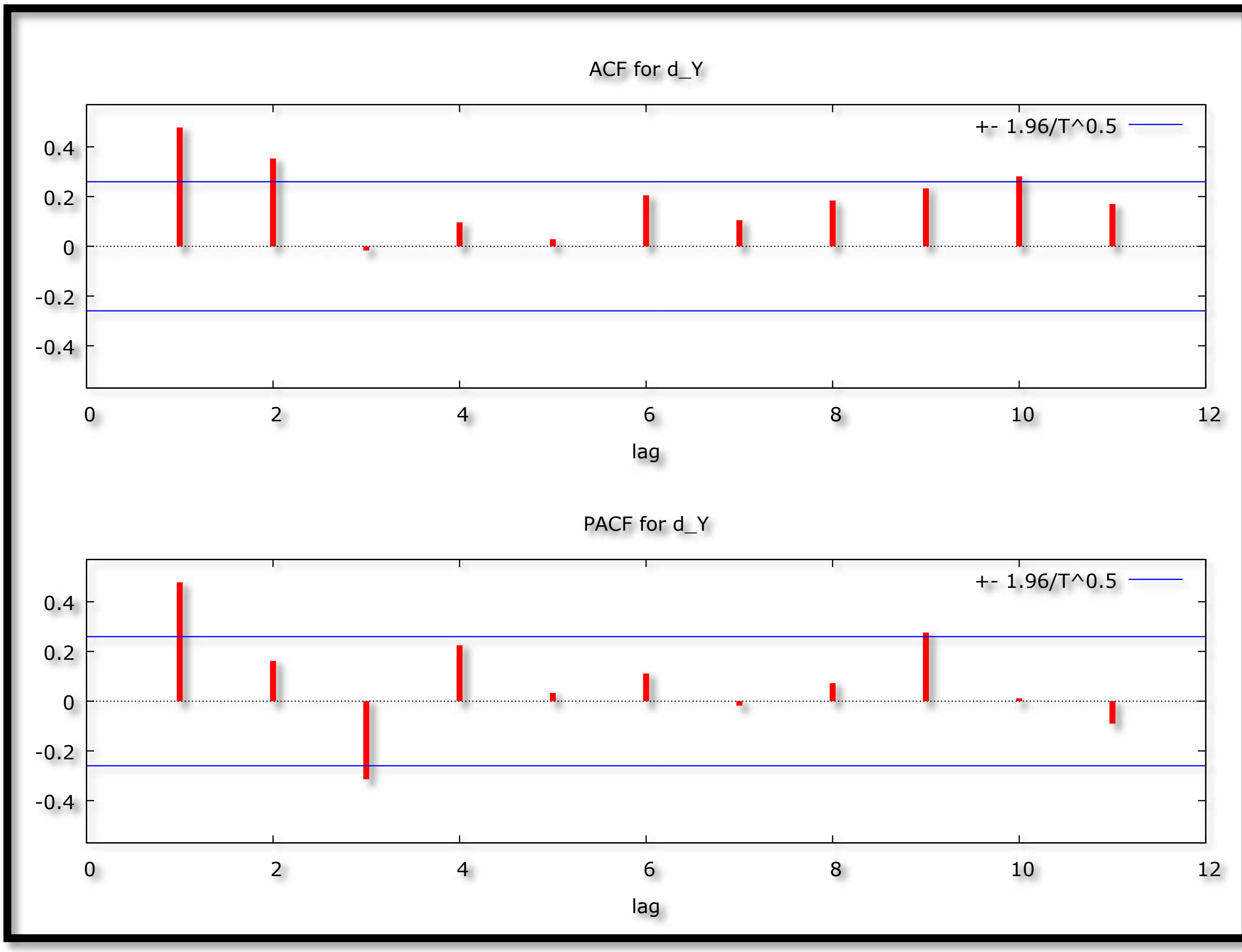


Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-4.366350	0.0009	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-4.829923	0.0014	-4.137279	@1%	Stationary
			-3.495295	@5%	Stationary
			-3.176618	@10%	Stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-1.723889	0.0802	-2.609324	@1%	Not stationary
			-1.947119	@5%	Not stationary
			-1.612867	@10%	Stationary

Figures 2 and 3 as well as tables 1 – 3 and tables 4 – 6, all indicate the non-stationarity of Y in both levels and after taking first differences respectively.

The Correlogram in (2nd Differences)

Figure 4

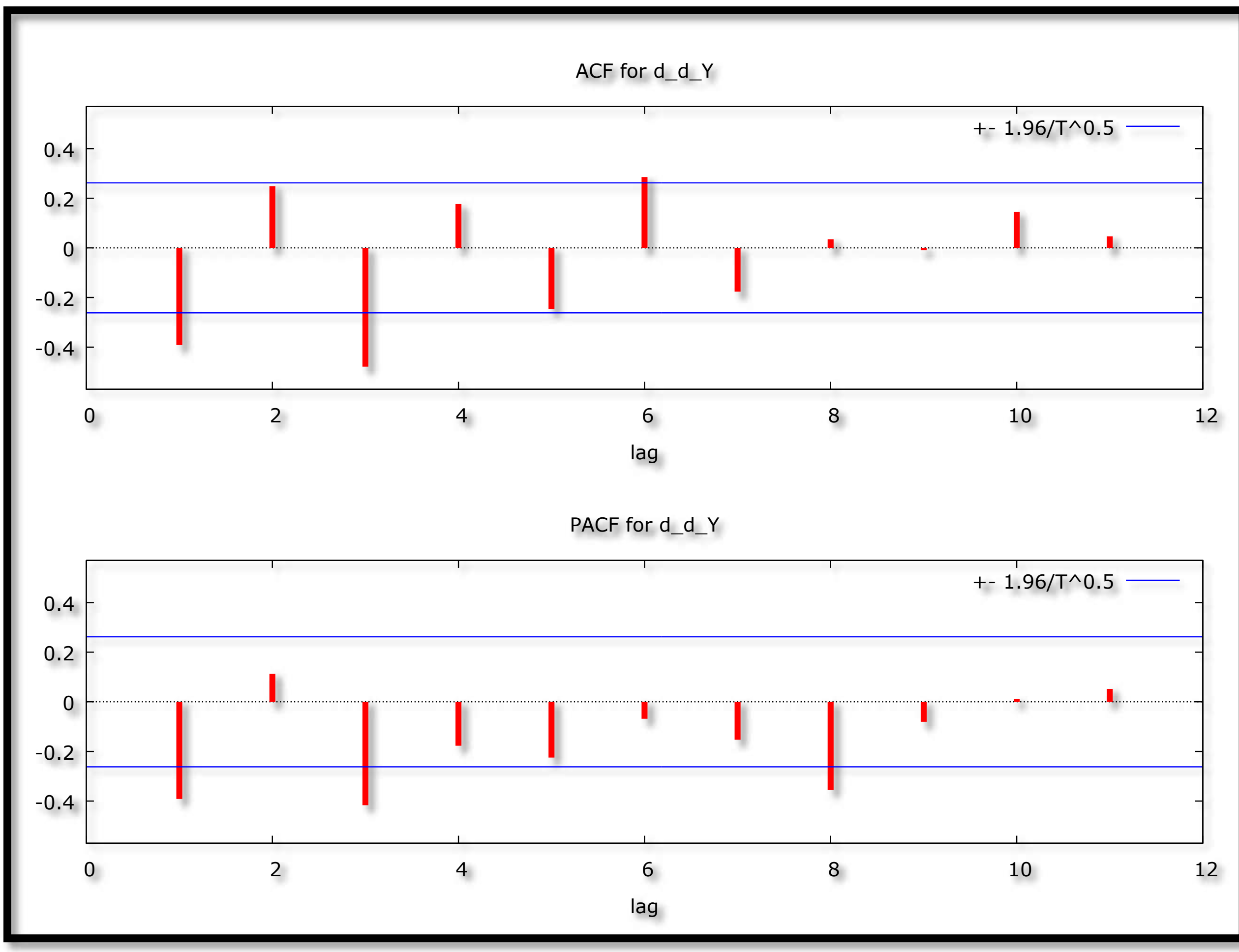


Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.772896	0.0000	-3.560019	@1%	Stationary
			-2.917650	@5%	Stationary
			-2.596689	@10%	Stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.711486	0.0000	-4.140858	@1%	Stationary
			-3.496960	@5%	Stationary
			-3.177579	@10%	Stationary

Table 9: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-6.820462	0.0000	-2.609324	@1%	Stationary
			-1.947119	@5%	Stationary
			-1.612867	@10%	Stationary

Figure 4 and tables 7 – 9 confirm that Y is stationary after taking second differences. Thus Y is an I (2) variable.

Evaluation of ARIMA models (without a constant)

Table 10

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 1)	589.9070	0.96927	1.5439	29.635	44.163	7.1836
ARIMA (1, 2, 2)	591.6601	0.95719	1.6738	29.47	43.999	7.1579
ARIMA (1, 2, 0)	594.3610	0.9815	1.6394	31.238	47.025	7.4152
ARIMA (1, 2, 3)	586.1932	0.87921	5.8464	27.536	41.091	6.7615
ARIMA (0,2, 1)	593.0066	0.94439	4.7982	31.301	46.208	7.5529
ARIMA (0, 2, 2)	592.1265	0.92318	5.9013	30.23	44.986	7.3011
ARIMA (3, 2, 1)	**581.0519**	**0.8653**	5.6265	25.44	39.115	6.432

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). In this paper, I only make use of the AIC in order to select the optimal model. Therefore, the ARIMA (3, 2, 1) model is chosen.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (3, 2, 1) Model

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-6.999771	0.0000	-3.562669	@1%	Stationary
			-2.918778	@5%	Stationary
			-2.597285	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-7.052709	0.0000	-4.144584	@1%	Stationary
			-3.498692	@5%	Stationary
			-3.178578	@10%	Stationary

Table 13: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion

ε_t	-6.906506	0.0000	-2.610192	@1%	Stationary
			-1.947248	@5%	Stationary
			-1.612797	@10%	Stationary

Tables 11, 12 and 13 show that the residuals of the ARIMA (3, 2, 1) model are stationary.

Stability Test of the ARIMA (3, 2, 1) Model

Figure 5

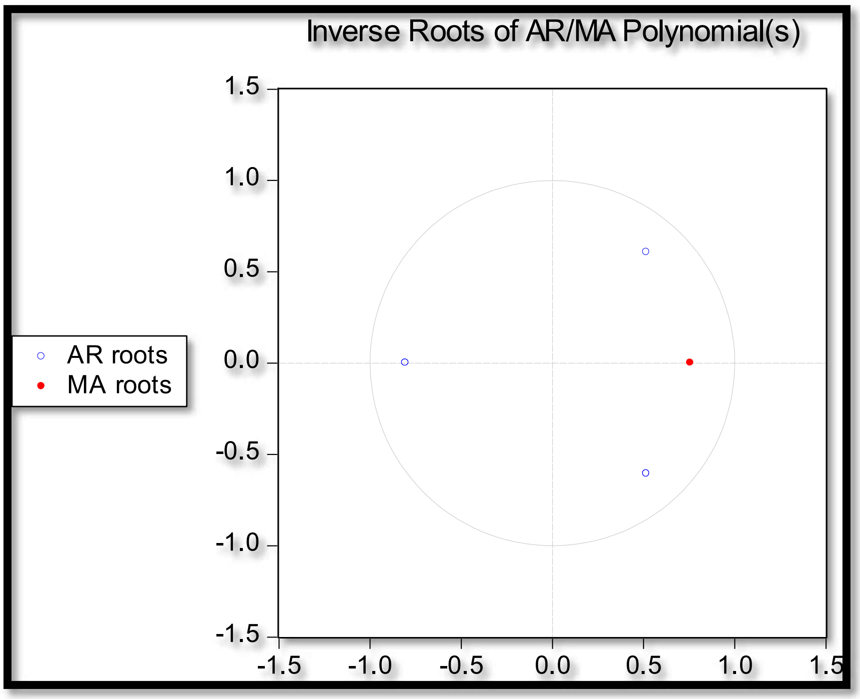


Figure 5 above reveals that the ARIMA (3, 2, 1) model is very stable because the corresponding inverse roots of the characteristic polynomial lie in the unit circle.

RESULTS & DISCUSSION

Descriptive Statistics

Table 14

Description	Statistic
Mean	462.86
Median	366
Minimum	95
Maximum	1508
Standard deviation	372.57
Skewness	1.4372
Excess kurtosis	1.1020

Table 14 above, shows that the mean is positive, i.e 462.86. The minimum GDP per capita is 95 and was realized in 1961. The maximum GDP per capita is 1508 and was realized in 2017. The skewness is 1.4372 and the most essential feature is that it is positive, indicating that the Y series is positively skewed and non-symmetric. Nyoni & Bonga (2017h) aver that the rule of thumb for kurtosis is that it should be around 3 for normally distributed variables and yet in this piece of work, kurtosis has been found to be 1.1020; indicating that the Y series is indeed not normally distributed.

Results Presentation[1]

Table 15

ARIMA (3, 2, 1) Model:

$$\Delta^2 Y_{t-1} = 0.2277\Delta^2 Y_{t-1} + 0.1896\Delta^2 Y_{t-2} - 0.4844\Delta^2 Y_{t-3} - 0.7446\mu_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [5]$$

P: (0.1270) (0.1444) (0.0001) (0.0000)

S. E: (0.149252) (0.129933) (0.127317) (0.137812)

Variable	Coefficient	Standard Error	z	p-value
AR (1)	0.227745	0.149252	1.526	0.1270
AR (2)	0.189633	0.129933	1.459	0.1444
AR (3)	-0.484357	0.127317	-3.804	0.0000***
MA (1)	-0.744627	0.137812	-5.403	0.0000***

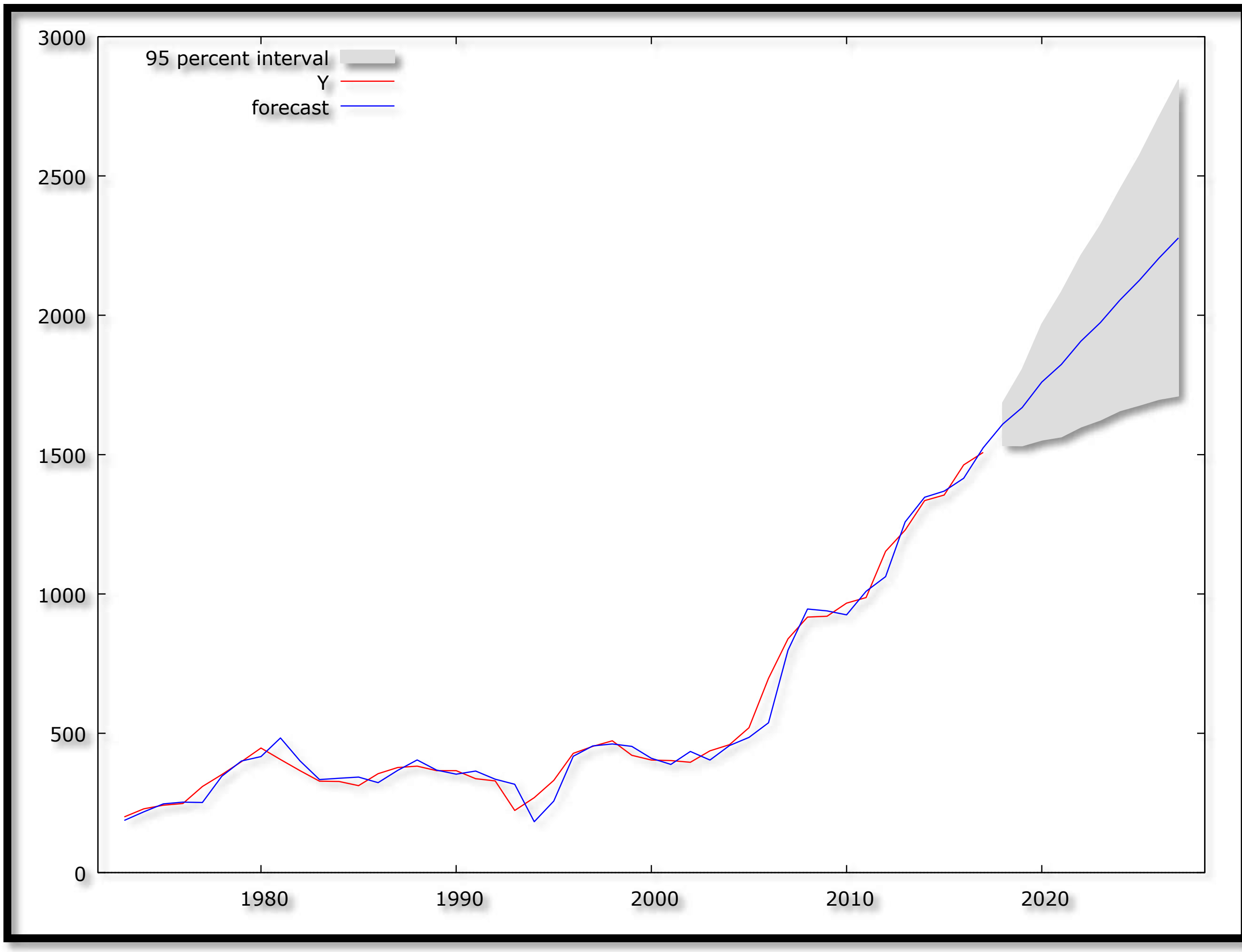
Interpretation of Results

Table 15 shows that the coefficient of AR (3) is negative and statistically significant at 1 % level of significance while the MA (1) coefficient is also negative and statistically significant at 1% level of significance. This indicates the importance of the AR(3) and MA(1) components in explaining GDP per capita in Kenya. The striking feature of these results is the importance of previous period shocks in explaining GDP per capita in Kenya, as reveal by the MA component. This implies that shocks to the Kenyan economy, for example, unpredicted political outcomes are quite pivotal in influencing the level of living standards in Kenya.

Forecast Graph

Figure 6

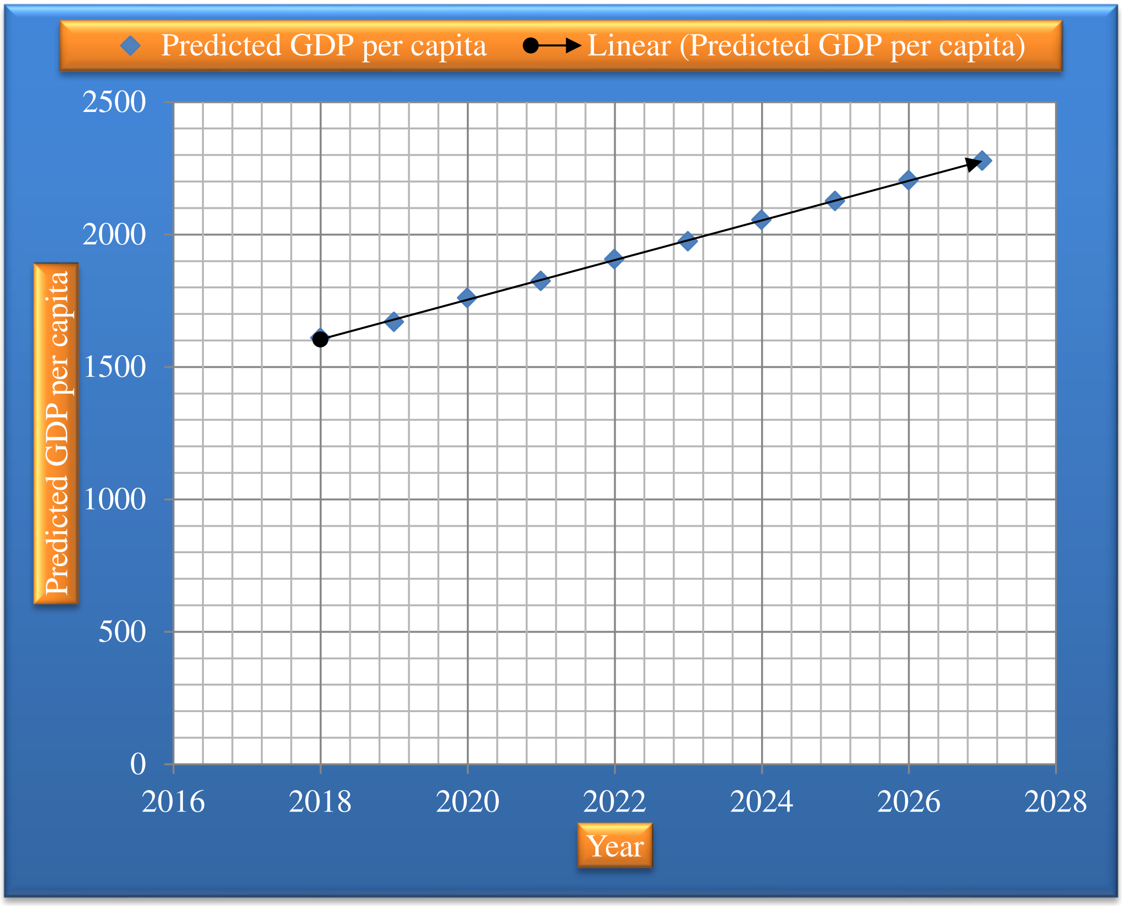
[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*



95 percent interval
Y
forecast
3000
2500
2000
1500
1000
500
0
1980
1990
2000
2010
2020

Predicted GDP per capita (for the next 10 years)

Figure 7



Figures 6 and 7, with a forecast range of 10 years; clearly reveal that Kenyan GDP per capita is set to improve over the next decade, especially if the current economic policy stance is either maintained or improved. By the end of the year 2020, Kenyan GDP per capita is expected to be approximately 1760.19 USD, which clearly confirms that Kenyan is being headed to the "promised land of milk and honey".

POLICY RECOMMENDATIONS

i. The CBK should continue to prioritize low and stable inflation and encourage growth through their monetary policy.
ii. Supporting long-term public debt sustainability through stables interest rates is also good policy stance and should be equally taken seriously.
iii. The CBK should continue to enhance financial access in the economy.

CONCLUSION

This study showed that the ARIMA (3, 2, 1) model is the optimal model to model and forecast GDP per capita in Kenya over the period 1960 – 2017. The study indicates that GDP per capita of Kenya is expected to rise in the next decade, as long as prudent macroeconomic management continues. This study is not the end of the road, but simply the starting point for policy makers in Kenya and the next thing is that they should act accordingly.

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