Is South Africa the South Africa we all desire? Insights from the Box-Jenkins ARIMA approach

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Abstract

Using annual time series data on GDP per capita in South Africa from 1960 to 2017, the study investigates GDP per capita using the Box – Jenkins ARIMA technique. The diagnostic tests such as the ADF tests show that South African GDP per capita data is I (1). Based on the AIC, the study presents the ARIMA (0, 1, 1) model. The diagnostic tests further show that the presented parsimonious model is indeed stable and quite reliable. The results of the study indicate that living standards in South Africa may improve but very slowly over the next decade, unless prudent macroeconomic management practices are exercised. The paper offers 5 main policy prescriptions in an effort to help policy makers in South Africa on how to promote and maintain the much awaited growth and development.

Key Words: Forecasting, GDP per capita, South Africa

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 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 (Nyoni & Bonga, 2018). 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, 2017).

The South African economy grew by 2% over the 3rd quarter of 2017 – its second consecutive quarter of growth following two quarters of contraction. The primary sector of the economy experienced strong growth of 14.8%, with both agriculture (44.2%) and mining (6.6%) sectors growing. Contractions were recorded in the utilities (5.5%), construction (1.1%), trade (0.4%) and government (0.7%) sectors. Over the three quarters of 2017, the economy grew by 1.1% compared with the corresponding period of 2016 (Amra, 2018). In South Africa, the economy slowed in 2018 and economic growth is projected to pick up slowly in 2019–20, driven by exports. Monetary policy is operating in a difficult environment of low growth and upward inflationary pressures. Fiscal space is tight (OECD, 2018). In South Africa, just like in any other country, the need for consistent and accurate GDP forecasts for the conduct of forward-looking monetary policy cannot be overlooked. This research attempts to model and forecast South African GDP per capita over the period 1960 – 2017.

LITERATURE REVIEW

Junoh (2004), using an econometric Artificial Neural Network (ANN) model; analyzed 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 China; modeled and forecasted GDP using ARIMA models based on annual data from 1962 to 2008 and established that the ARIMA (4, 1, 0) model was the optimal model. Bipasha & Bani (2012) studied GDP growth rates of India relying on ARIMA models using annual data from 1959 to 2011 and revealed that the ARIMA (1, 2, 2) model was the optimal model to forecast GDP growth in India. Dritsaki (2015) looked at real GDP in Greece basing on the Box-Jenkins ARIMA methodology during the period 1980 – 2013 and concluded that the ARIMA (1, 1, 1) model was the optimal model. Wabomba *et al* (2016), in Kenya, modeled and forecasted GDP using ARIMA models with an annual data set ranging from 1960 to 2012 and concluded that the ARIMA (2, 2, 2) model was the optimal 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 shown using a backward shift operator as follows:

$$\emptyset(B)(1-B)^d Y_t = \theta(B)\mu_t \quad [1]$$

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

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

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

and

$$(1-B)^d Y_t = \Delta^d Y_t \quad [4]$$

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, 2018).

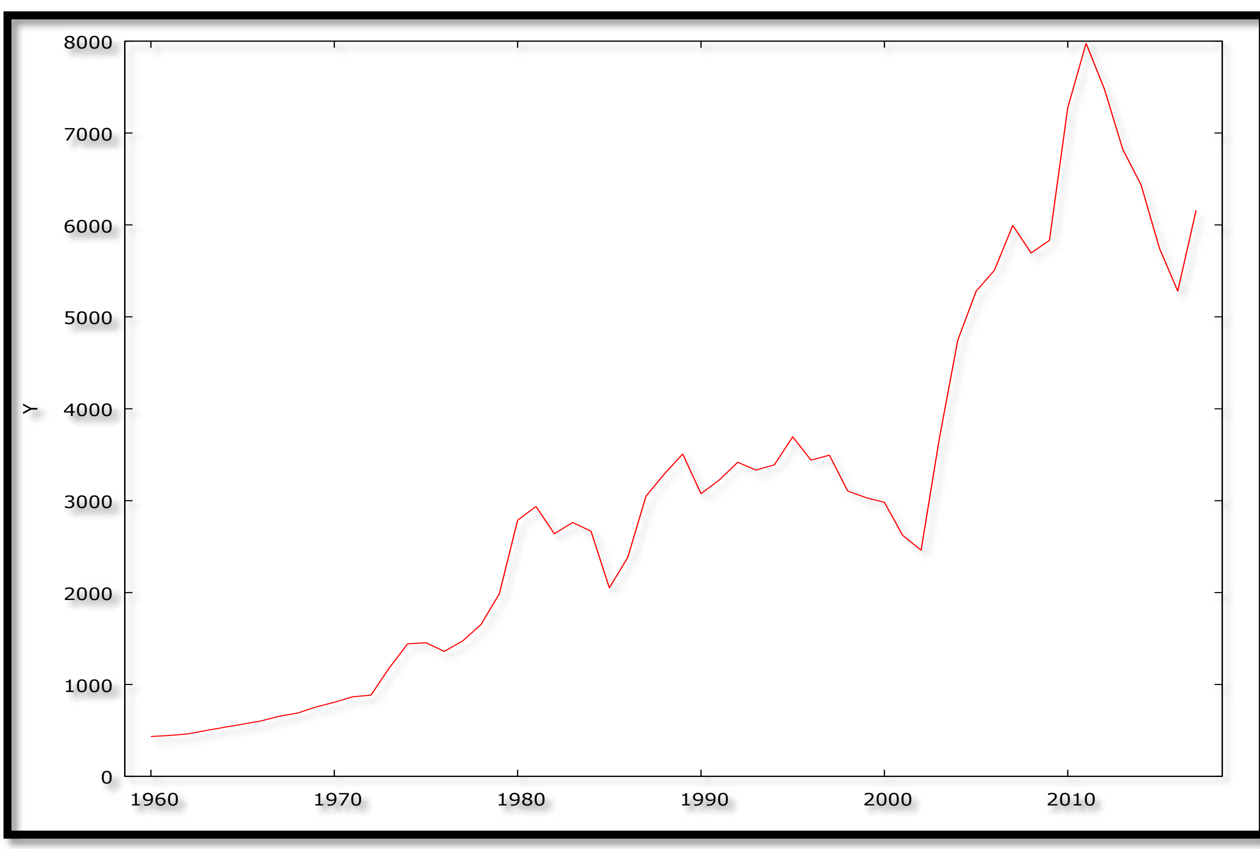
Data Collection

Our paper is based on 58 observations (i.e, 1960 – 2017) of annual GDP per capita in South Africa. The data employed here was taken from the World Bank online database, which was chosen based on its integrity and credibility in data collection and management.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

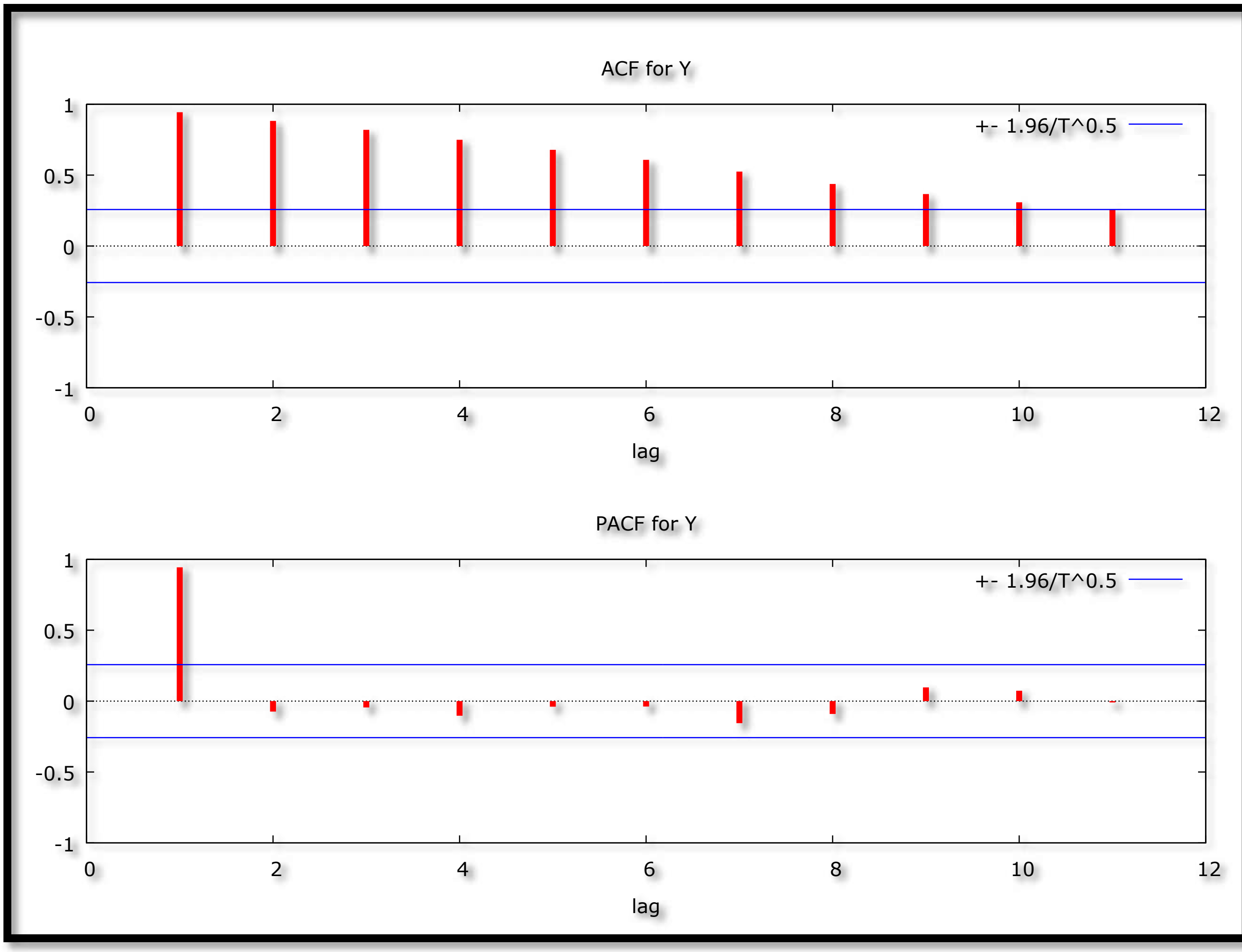
Figure 1



The South African GDP per capita variable, as shown above is not stationary as it is trending upwards over the period under study and this indicates that its mean 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	-0.499816	0.8830	-3.555023	@1%	Not stationary
			-2.915522	@5%	Not stationary
			-2.595565	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-3.476183	0.0519	-4.130526	@1%	Not stationary

			-3.492149	@5%	Not stationary
			-3.174802	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	1.135681	0.9320	-2.607686	@1%	Not stationary
			-1.946878	@5%	Not stationary
			-1.612999	@10%	Not stationary

As shown in figure 2 as well as tables 1 – 3 above, the GDP capita series is non-stationary in levels and thus not I (0).

The Correlogram (at 1st Differences)

Figure 3

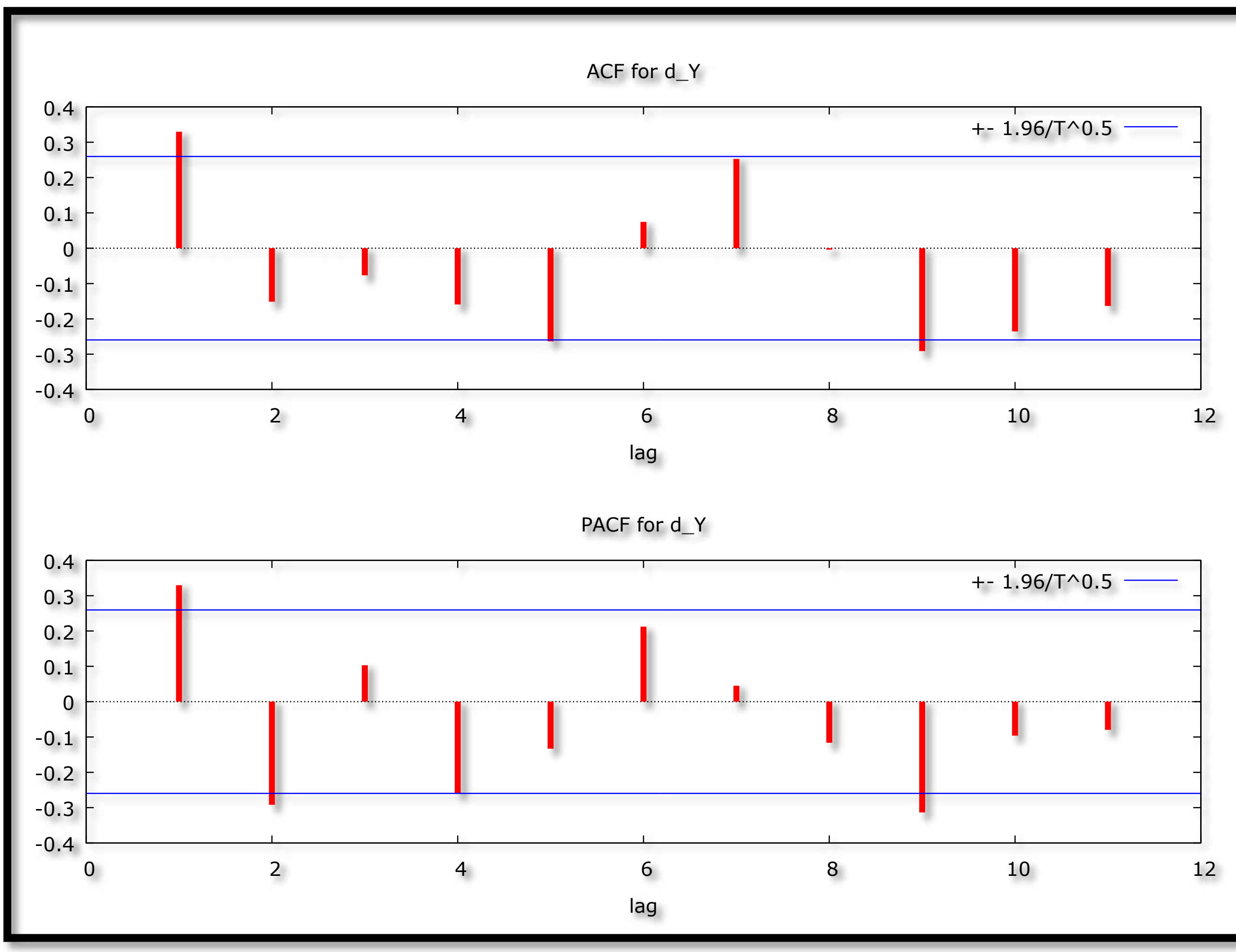


Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-5.740150	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary

			-2.595565	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-5.688872	0.0001	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Y	-5.380311	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Figure 3 and tables 4 – 6, all illustrate that the Y series became stationary after taking first differences; hence it's I (1).

Evaluation of ARIMA models (without a constant)

Table 7

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	846.6364	0.90114	69.985	267.49	384.27	8.3716
ARIMA (1, 1, 0)	851.5172	0.93737	68.399	274.37	409.15	8.5609
ARIMA (2, 1, 0)	848.1174	0.91457	86.381	272.56	389.45	8.5777
ARIMA (0, 1, 1)	**844.6429**	0.90105	69.424	266.94	384.28	8.3586

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will only consider the AIC in order to select the best model. Therefore, the ARIMA (0, 1, 1) model is chosen.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 1, 1) Model

Table 8: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-7.220116	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 9: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-4.130526	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

Table 10: without intercept and trend & intercept

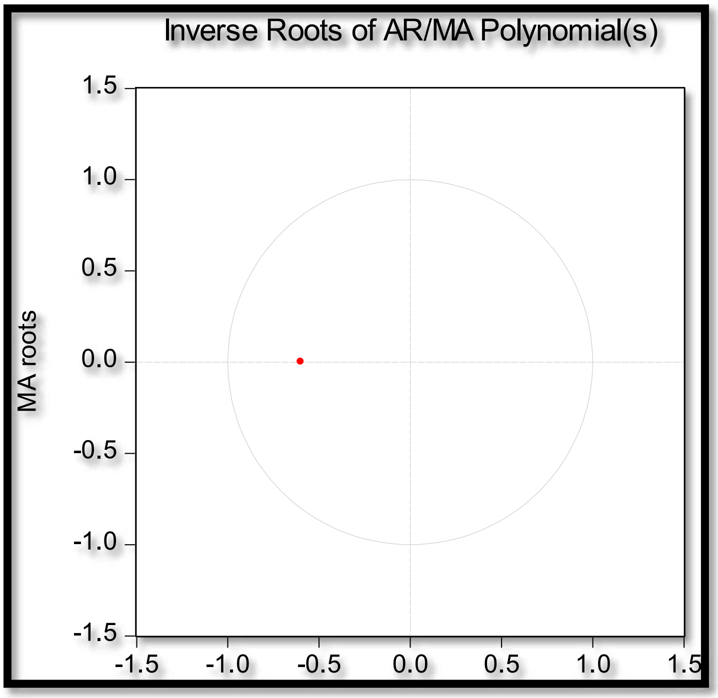
Variable	ADF Statistic	Probability	Critical Values		Conclusion

ε_t	-7.039447	0.0000	-2.606911	@1%	Stationary
			-1.946467	@5%	Stationary
			-1.613062	@10%	Stationary

Tables 8 – 10, all reveal that the residuals of the chosen optimal model, the ARIMA (0, 1, 1) model are stationary.

Stability Test of the ARIMA (0, 1, 1) Model

Figure 4



As shown in the figure above, the ARIMA (0, 1, 1) model is very stable because the corresponding inverse root of the characteristic polynomial lies in the unit circle.

FINDINGS

Descriptive Statistics

Table 11

Description	Statistic
Mean	3068.9
Median	2959
Minimum	434
Maximum	7976
Standard deviation	2070.2
Skewness	0.60422
Excess kurtosis	-0.54158

The mean GDP per capita is positive, i.e 3068.9 USD. The minimum GDP per capita is 434 USD while the maximum is 7976 USD. Skewness is 0.60422 and it is positive, indicating that the South African GDP per capita series is positively skewed and non-symmetric. Kurtosis is -0.54158, indicating that the Y series is not normally distributed.

Results Presentation[1]

Table 12

ARIMA (0, 1, 1) Model:				
$\Delta Y_{t-1} = 0.590302\mu_{t-1} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots [5]$				
P: (0.00000017)				
S. E: (0.112878)				
Variable	Coefficient	Standard Error	z	p-value
MA (1)	0.590302	0.112878	5.23	0.00000017***

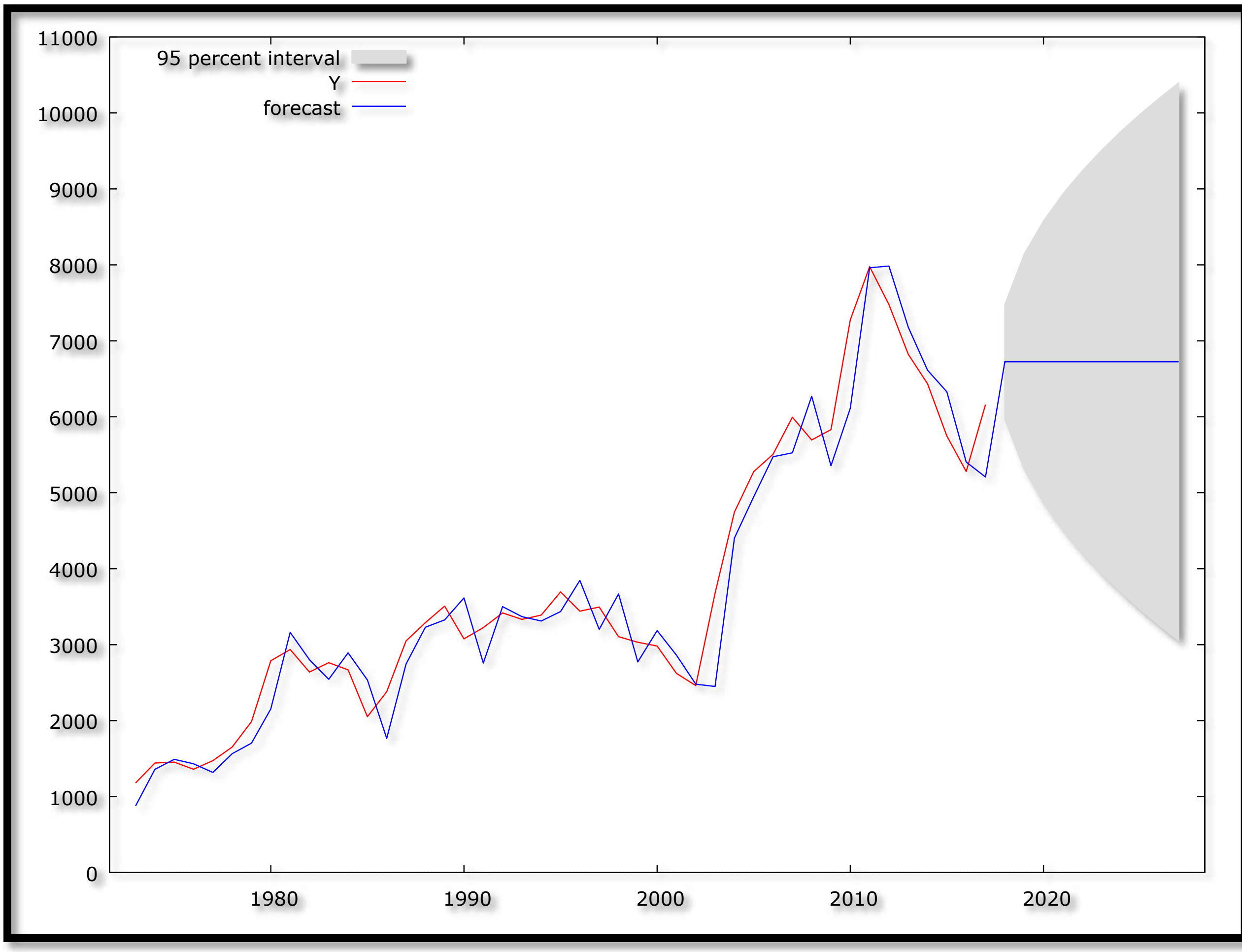
Interpretation of Results

The coefficient of the MA (1) component is positive and statistically significant at 1% level of significance. The implication is that unobserved shocks to GDP per capita in South Africa have a strong positive impact on South African living standards. Examples of such unobserved shocks may include the unexpected removal of former president Mr. Zuma from Office and the coming in of current leadership led by President Ramaphosa. Many South Africans arguably believe that the coming in of President Ramaphosa will bring positive changes in the economy. In fact our model indicates that a 1% increase in such shocks will lead to approximately 0.59% increase in GDP per capita. This is particularly reasonable in the case of South Africa where the previous regime led by Mr. Zuma was allegedly corrupt and failed to stimulate the much awaited economic growth in South Africa. The new political leadership, led by President Ramaphosa has gained credibility and won the confidence of economic agents and is likely to succeed in implementing its policies.

Forecast Graph

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

Figure 5



South Africa's GDP per capita is expected to be hovering around 6724.19 United States Dollars over the next decade unless there are serious policy changes in terms of improving the general living standards of South Africans. President Ramaphosa and his team have a cumbersome task of improving the general living standards of South Africans. Below are the main policy actions that are needed to ensure a better South Africa for all:

Policy Implications

i. There is need to prioritize economic growth ahead of politically motivated objectives.
ii. There is need to address upward pressures on inflation in South Africa. Price stability should not be undermined.
iii. Good governance and rule of law are compulsory if South Africa is to improve her living standards.

iv. Policy makers in South Africa should also thrive to maintain a conducive investment climate for both domestic and foreign investors.
v. There is need to educate and train South Africans on the importance of entrepreneurship in order to reduce both unemployment and extreme poverty.

CONCLUSION

This research revealed that the ARIMA (0, 1, 1) model is the optimal model to model and forecast GDP per capita in South Africa over the period 1960 – 2017. The research indicates that GDP per capita of South Africa is expected to be around 6724.19 USD over the next decade. The study is envisaged to assist policy makers in planning for a better future for South Africans.

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