Forecasting the GDP per Capita for Egypt and Saudi Arabia Using ARIMA Models

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Abstract

Annual time series data is used to forecast GDP per capita using the Box-Jenkins Autoregressive-Integrated Moving-Average (ARIMA) model for the Egyptian and Saudi Arabian economies. The fitted ARIMA model is tested for per capita GDP forecasting of Egypt and of Saudi Arabia for the next ten years. Conclusions convey that the most accurate statistical model as in previous literature that forecast GDP per capita for Egypt and for Saudi Arabia is ARIMA (1,1,2) and ARIMA (1,1,1) respectively. The diagnostic tests reveal that the two models presented individually are both stable and reliable.

Keywords: time series, Egypt, Saudi Arabia, forecasting, ARIMA, GDP per capita, residuals analysis

JEL Classification: C53, O11, O53

1. Introduction

Policy makers and economists continuously assess the healthiness status of any economy using the Gross Domestic Product (GDP) as a measure of economic growth, a determinant of a country's standard of living, and an asset distributor for efficient production. GDP, a broadcast measure of total output of an economy (Kimberly, 2008), is defined as the total market value of all *final* goods and services produced by all people within an economy. In order to avoid double counting, GDP only takes into account the production of final goods and services rather than intermediate goods. Economists such as Rostow, Baran, and Leibenstient use GDP per capita, an index of economic growth, to compare the wealth of one country with another (Pooja, 2015). GDP per capita is calculated by dividing the GDP by the total population of the country in question.

Long run economic growth as defined in various scholarly literature is a sustained increase in per capital national output based on a nation's ability to invest in ensuring the efficient use of resources. This is paralleld by a quantitative increase in the monetary value of goods and serviced produced in an economy within a given year (Nyoni & Bonga, 2018a). Simply, the faster the pace of productivity growth, the more sustainable the economy can ensure a higher growth rate of Gross Domestic Product GDP (Junoh, 2004). Boosting productivity growth has some conditionalities such as (1) improving the quality of workforce through education and training, (2) equipping the workers with more and better capital such as computers and (3) improving technology so that the given input produces greater output (Blinder, 2000). Forecasting GDP per capita using econometric modelling techniques is significant both theoretically and practically, on the country development level and for the forward-looking monetary policies. This line of thinking depends on the availability of real-time data, specifically when determining the initial conditions of economic activity.

The objective of this paper is to empirically develop a linear model for forecasting GDP per capita of Egypt and Saudi Arabia based on Box and Jenkins (1976) Univariate Autoregressive Integrated Moving Average model (ARIMA). How such models can best fit the Egyptian and Saudi Arabian GDP per capita is exposed by practically experimenting with the ARIMA model. The rest of the paper is organized into five parts: literature review, materials & methods used to achieve the objectives of this paper, results and discussion of results, and conclusion.

2. Literature Review

Forecasting GDP per capita using ARIMA has proved its appropriateness in previous literature as evident in the empirical works of Bhuiayan et al (2008), Ning et al (2010), Maity and Chatteriee (2012). Estimated GDP per capita dynamics uses ARIMA models invented by Box and Jenkins in 1976 (Abonazel and Abd-Elftah, 2019). In the case of non-stationary series, ARIMA models, an extension of ARMA models are used. The ARIMA (p, d, q), with three parameters, p: order of autoregressive, d: the degree of differencing, and q: the order of moving average, is an econometric technique for short-term time-series forecasting (Chinwuba and Ibrahim, 2013).

With the application of ARIMA, the Vector Autoregression model (VAR), and the first-order Autoregression AR (1), time series data for regional GDP per capita has evidenced to be an effective economic experimential tool for both advanced and emerging countries be it annual or quarterly data. Examples include Sweden from 1993 to 2009 and China from 1962 to 2008, establishing an optimal model of ARIMA (4,1,0) (Haonon 2013). Zakai used quarterly date from 1953 to 2012 to forecast Pakistan's GDP with the aid of ARIMA (1,1,0) with results conveying the likely increase in GDP for the years 2013-2025 (Zakai 2014). India's GDP growth rates were forecasted using annual data from 1959 to 2011 and results conveyed that an ARIMA (1,2,2) model was the best fit (Maity, B., & Chatterjee, B 2012). With the aid of data from 1980 to 2013, Economist Dritsaki in 2015 forecasted Greece's real GDP rate using ARIMA (1,1,1) model; statistical results provided a steadily improving forecasted Greek GDP rate.

Economists have also extended the ARIMA models into nonlinear threshold autoregressive models SETAR models to forecast country GDPs such as modelling the Canadian GDP from 1965 to 2000 (Feng and Liu 2003); a comparison between one-way (actual data used to predict every period) and multi-way forecasting (previous periods' predictions are used as part of the forecasting equation) has offered proof that both methods are reliable, but in reality, the multi-way forecasting is a more practical approach. In addition, South African GDP forecast using monthly data over the period 1970 to 2000 has proved that the "Bayesian Vector error correction model BVECM has been the most accurate out of sample forecasts" (Gupta 2007). Economists such as Camcho and Martinez-Martin have developed a single index US business cycle dynamic factor model originally developed by Aruba and Diebold in 2010 to forecast real GDP growth rate in the US. Using time series modelling, Africa's GDP in 20 countries over the period 1990 to 2016 proved an "increasing GDP growth rate where average speed of the economy of Africa will be approximately 5.52% and the GDP could hover between $2185.21 billion and $ 101861.18 billion" (Uwimana et al 2018).

Limitations in finding previous empirical research literature on forecasting per capita GDP growth rate specifically for Saudi Arabia and Egypt was evident. One study done by Abonael and Abd-Elftah (2019) proved that Egypt's forecasted GDP growth rate is ARIMA (1,2,1). This paper is signficicant because it forecasts the GDP per capita for two individual emerging countries, Egypt and Saudi Arabia, predicted to have high GDP growth rates in the future. Most ARIMA model research papers are technical and experimential and focus on one individual country. This paper holds the same nature however it sets a platform for further research, whether regarding an analysis of each individual country on its own and how policy makers will manage to work around the forecasts, and/or setting a starting point for an analytical comparison between the policies and macroeconomic performance of the two countries.

3. Data Description

Annual GDP per Capita (GDPC) data (constant 2010 dollars) of Egypt from 1960 to 2018 and Saudi Arabia from 1968 to 2018 (due to unavailability of data) is used (Note 1), with 59 observations for Egypt and 51 observation for Saudi Arabia satisfying the Box-Jenkins approach for time series forecasting of having over 50 observations (Chatfield, 2016). Based on such data, two ARIMA models one for each country is developed and then put in action to forecast the GDPC for the next ten years (from 2018 to 2030).

4. Research Methods

This paper uses Box and Jenkins' (Note 2) methodology to highlight GDP future rates for both Egypt and Saudi Arabia. In time series analysis, the Box-Jenkins applies ARIMA models (univariate time series models) to find the best fit of a model to past values. This is conducted by estimating the tested variable entirely on its own inertia (i.e. based on its previous values or errors or a combination of the two depending on the circumstances that best fit the situation).

Using ARIMA models to estimate a time series variable means estimating that variable entirely on its own inertia (i.e. based on its previous values or errors or a combination of the two depending on the circumstances that best fit the situation). Box and Jenkins (1976) named after statisticians George Box and Gwily Jenkins methodology has been to highlight GDP future rates, an integral part of calculating per capita GDP (Dritsaki, 2015). In time series analysis, the Box-Jenkins applies ARIMA models to find the best fit of a time series model to past values of a time series. Steps for using the ARIMA model are highlighted as follows:

(1) Model Identification: The stationary status of the data is determined (d) along with data plotting, partial autocorrelations (PACF), autocorrelations (ACF), and other information, to determine (p and q). In statistical literature, ARIMA models involve:

(a) Autoregressive (AR) process of order p, AR (p) expressed as

$X_t = c + \alpha_1 X_{t-1} + \alpha 2 X_{t-2} + \cdots + \alpha p X_{t-p} + \varepsilon_t$; $t = 1{,}2, \ldots T$, (1) where εt is the error term, a white noise process

(b) Differencing process: $E(\varepsilon t) = 0$ and $var(\varepsilon t) = \sigma\ 2$; i.e. $\varepsilon t \sim iid\ N(0, \sigma\ 2)$.

(c) Moving-Average (MA) process: A time series $\{X_t\}$ is said to be a moving-average process of order q, MA (q), if: $X_t = \varepsilon_t - \theta 1 \varepsilon_{t-1} - \theta 2 \varepsilon_{t-2} - \cdots - \theta q \varepsilon t{-}q$.

(2) Model Estimation: Maximum likelihood estimation (MLE) or non-linear least-squares estimation are used.

(3) Diagnostic Checking: This step checks that the residuals are constant in mean and variance over time. Plotting PACF and ACF of the residuals could identify misspecification. If the estimation is inadequate, some adjustments in step one, model identification, should be considered.

(4) Forecasting: Once the selected ARIMA model conforms to the specifications of a stationary univariate process, the model is tested for forecasting.

5. Results

5.1 Step One: Model Identification: Testing for Stationarity

Figure 1 and Figure 2 provide a preliminary analysis using visual time plot inspection of GDPC and they prove the nonstationary nature of GDPC for both Egypt and Saudi Arabia. (Note 3)

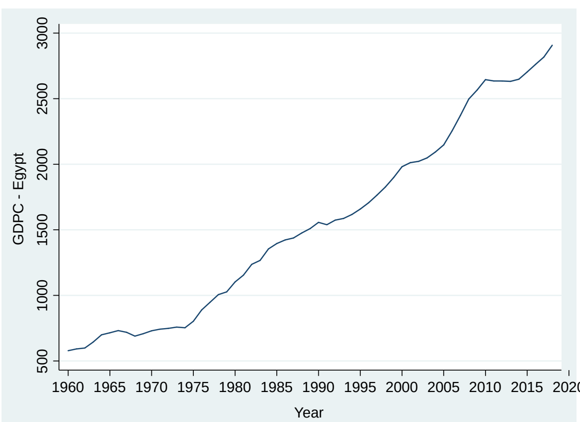

Figure 1. Time Series Plot of GDPC - Egypt, 1960 – 2018b

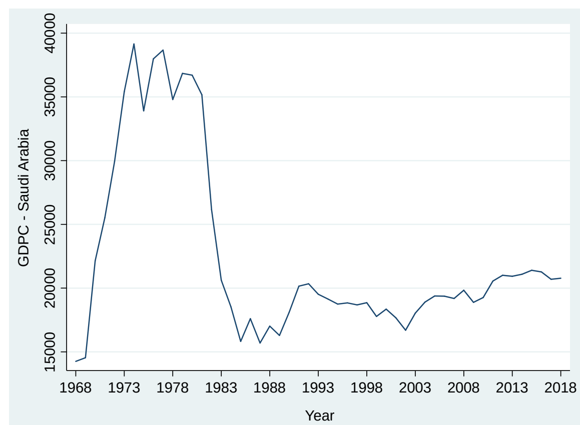

Figure 2. Time Series Plot of GDPC - Saudi Arabia, 1968 – 2018

Source: Author's calculations

The figures confirm a seasonal trend that can be transformed into a logarithmic expression. Nonstationary behavior of the series is further confirmed by Augmented Dickey and Fuller (ADF) unit root test.

The null and the alternatives of ADF are:

Ho: time series have unit root (non-stationary); if the p-value from ADF>0.05, H_0 is accepted.

Ha: time series do not follow unit root (stationary)

ADF in Table One conveys that although the GDPC proved its nonstationary at the data level, for Egypt and Saudi Arabia, it flexibly transforms into stationary at first difference.

Table 1. Unit Root Test

Variable Name	Level		First Difference		Integration Degree
	Statistics	p-value	Statistics	p-value	
GDPC -Egypt	2.407	0.9903	-3.836	0.0002	**I (1)**
GDPC-Saudi Arabia	-1.572	0.0612	-4.952	0.0000	**I (1)**

Source: Author's calculations

In line with the ADF test, the ACF and PACF plots are used to check the non-stationary behavior of the GDPC series. Figure Three and Four (in the appendix) confirm that GDPC series of Egypt and Saudi Arabia are not stationary, since all p-values of Q-test are less than 0.05. To reach stationarity, the differencing as practiced in the construction of ARIMA models, is used. Figures 3 and 4 display GDPC series for both Egypt and Saudi Arabia at first difference with their stationarity, non-trending pattern. This result is consistent with Table 1, consequently d=1.

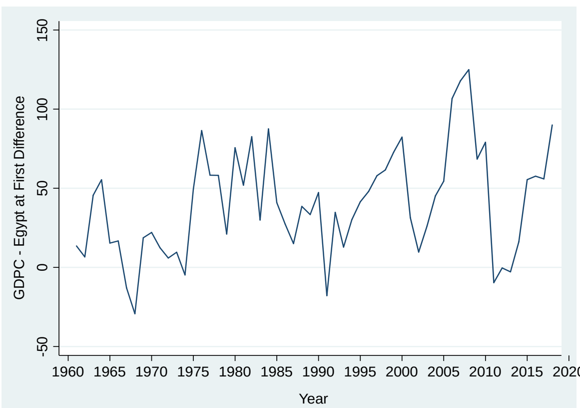

Figure 3. Time Series Plot of GDPC - Egypt at First Difference, 1968 – 2018

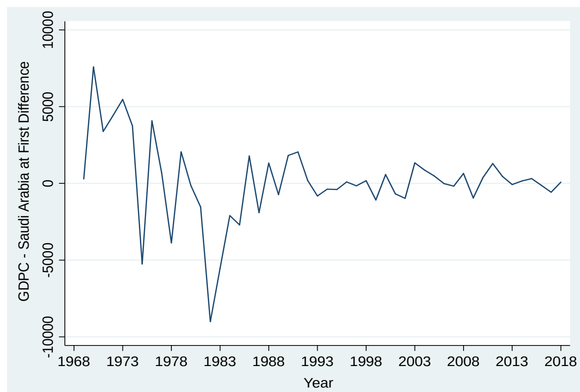

Figure 4. Time Series Plot of GDPC - Saudi Arabia at First Difference, 1968 – 2018

Source: Author's calculations

In order to identify the value of other two parameters p and q of ARIMA model, the PACF and ACF of the differenced GDPC series for both Egypt and Saudi Arabia are considered.

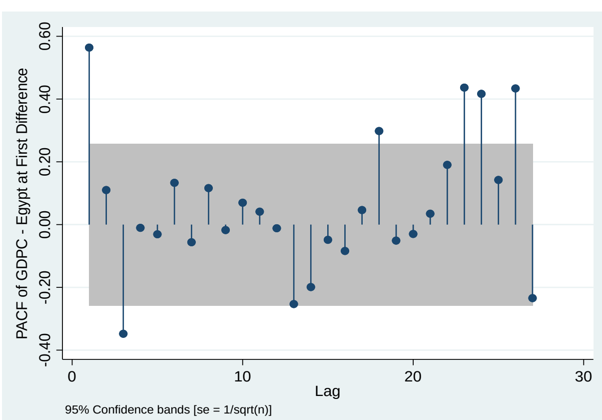

Figure 5. PACF of GDPC – Egypt at first difference

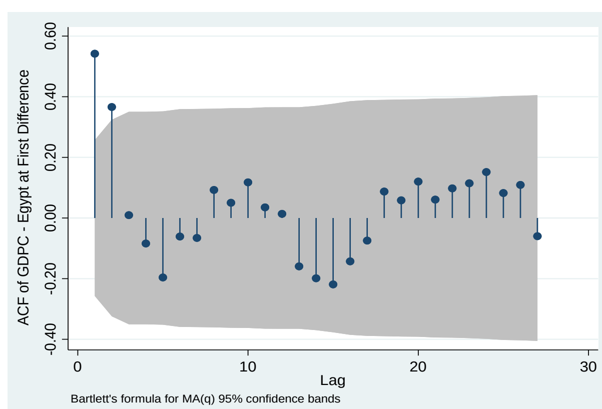

Figure 6. ACF of GDPC - Egypt at first difference

Source: Author's calculations

The first lag value of PACF is statistically significant as shown in Figures 5 and 6 respectively (in comparison to PACF at all other lags) suggesting a possible AR(1) model for GDPC series of Egypt. ACF first and second lags are statistically significant relative to all subsequent insignificant autocorrelations suggesting a possible MA (2) model for GDPC series of Egypt. Therefore, the model best fit for GDPC series of Egypt is ARIMA (1, 1, 2)

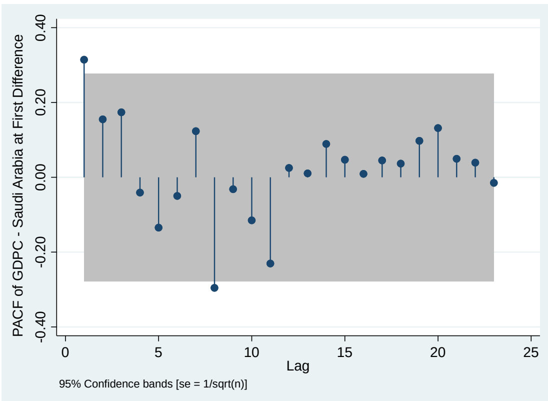

Figure 7. PACF of GDPC – Saudi Arabia at first difference

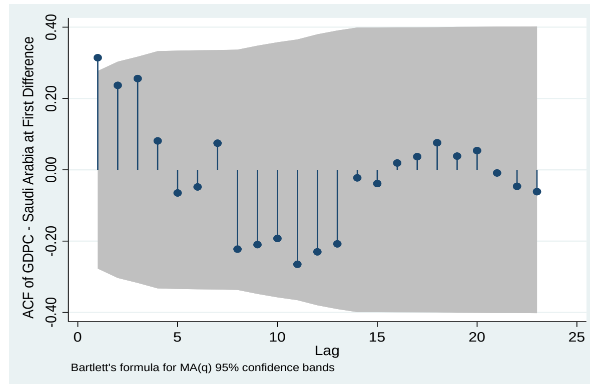

Figure 8. ACF of GDPC - Saudi Arabia at first difference

Source: Author's calculations

For Saudi Arabia, the Figures 7 and 8 display the statistical significance of the first lag value of PACF, where all other lags are not statistically significant; this suggests a possible AR(1) model for GDPC series of Saudi Arabia. The suggested moving average is MA(1) since the first lag of ACF is statistically significant, and all other subsequent autocorrelations are not. In sequence, the most fit model for GDPC series of Saudi Arabia is ARIMA (1, 1, 1).

5.2 Step Two: Model Estimation

5.2.1 Egyptian Model

Table 2. Parameter estimates of ARIMA (1, 1, 2), Egypt, 1960 -2018

D. GDPC	**Estimate**	**Standard Error**	**P-value**
Constant	40.416	8.214	0.000
AR – L1.	0.321	0.248	0.195
MA – L1.	0.209	0.275	0.446
MA – L2	0.392	0.174	0.024
Model Summary			
Wald chi^2 (3)	20.14	P-value of Wald	0.0002

Source: Author's calculations

Table 2 presents the MLE estimates modeling the results of ARIMA (1, 1, 2). In overall, the model is statistically significant at 1% level of significance; although the coefficients estimate of AR (1) and MA (1) are not significant, the coefficient estimate MA (2) is statistically significant at 5% level of significance. The above model is compared to tentative ARIMA models to select the best model for the data using different goodness-of-fit measures (AIC and BIC). The results are presented in Table 3.

Table 3. Evaluation of various ARIMA models, Egypt, 1960 -2018

Model	AIC	BIC
ARIMA (1, 1, 2)	555.1534	565.4556
ARIMA (1, 1, 1)	558.8856	567.1274
ARIMA (3, 1, 1)	555.4591	567.8218
ARIMA (3, 1, 2)	557.2417	571.6648

Source: Author's calculations

According to the results in Table 3, the best model is ARIMA (1, 1, 2), because it has the minimum values of AIC, and BIC. Therefore, the estimated regression equation of ARIMA (1, 1, 2) model is:

$$\Delta\widehat{\mathrm{GDPC}}_t = 40.416 + 0.321\Delta\widehat{\mathrm{GDPC}}_{t-1} + 0.209\hat{\varepsilon}_{t-1} + 0.392\hat{\varepsilon}_{t-2},$$

5.2.2 Saudi Arabia Model

Table 4. Parameter estimates of ARIMA (1, 1, 1), Saudi Arabia, 1968 -2018

D. GDPC	Estimate	Standard Error	P-value
Constant	220.627	780.819	0.778
AR – L1.	0.739	0.188	0.000
MA – L1.	-0.475	0.260	0.068
Model Summary			
Wald chi2 (3)	33.88	P-value o Wald	0.000

Source: Author's calculations

Table 4 presents the modeling results of ARIMA (1, 1, 1) process estimated by MLE; the coefficients estimate of AR (1) and MA(1) are significant, at 1% and 10% level of significance respectively. In sum, the model has proved to be statistically significant at 1% level of significance. The best model for Saudi Arabia as shown in table 5 is ARIMA (1,1,1) where the minimum values of AIC and BIC are evident.

Table 5. Evaluation of various ARIMA models, Saudi Arabia, 1968 -2018

Model	AIC	BIC
ARIMA (1, 1, 1)	930.8425	938.4906
ARIMA (8, 1, 1)	931.293	952.3253

Source: Author's calculations

The estimated regression equation of ARIMA (1, 1, 1) model therefore is:

$$\Delta\widehat{\mathrm{GDPC}}_t = 220.627 + 0.739\Delta\widehat{\mathrm{GDPC}}_{t-1} - 0.475\hat{\varepsilon}_{t-1},$$

5.3 Step Three: Diagnostics Checking

For more detailed structuring considerations, diagnostic checking of ARIMA models are examined using the autocorrelation plots of the residuals; the smaller the value of full and/or partial autocorrelations, the move-forward to generating forecasting schemes; the larger the autocorrelations, the urge to re-estimate the values of p and/or q are required.

5.3.1 Egypt Model

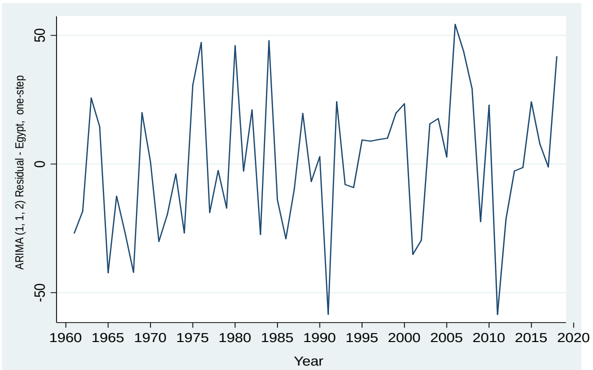

Figure 9. Time Series Plot of ARIMA (1, 1, 2) Residuals - Egypt

Table 6. Unit Root Test of ARIMA (1, 1, 2) Residuals - Egypt

Variable Name	Level	
	Statistics	P-value
ARIMA (1, 1, 2) Residuals	-7.272	0.000

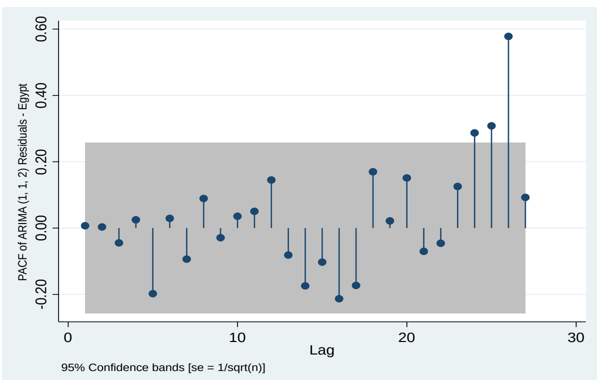

Figure 10. PACF of ARIMA (1, 1, 2) Residuals - Egypt

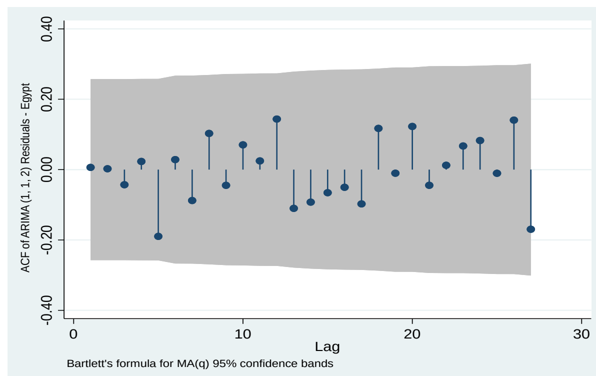

Figure 11. ACF of ARIMA (1, 1, 2) Residuals - Egypt

Source: Author's calculations

For Egypt, the correlogram of the PACF for the residuals is not so flat showing some significant at lags 24, 25, and 26 in figure 10, but because of parsimony, such lags will not be considered. On the other hand, the ACF for residuals in Figure 13 is flat which indicates that all information is captured. Therefore, the forecast will be based on this model **ARIMA (1, 1, 2).**

5.3.2 Saudi Arabia Model

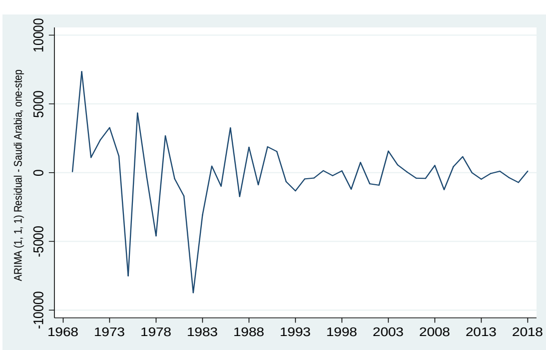

Figure 12. Time Series Plot of ARIMA (1, 1, 1) Residuals - Saudi Arabia

Table 7. Unit Root Test of ARIMA (1, 1, 1) Residuals - Saudi Arabia

Variable Name	Level	
	Statistics	P-value
ARIMA (1, 1, 1) Residuals	-6.984	0.000

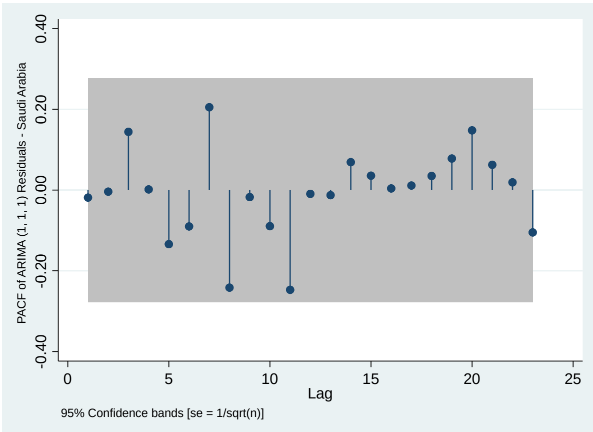

Figure 13. PACF of ARIMA (1, 1, 1) Residuals - Saudi Arabia

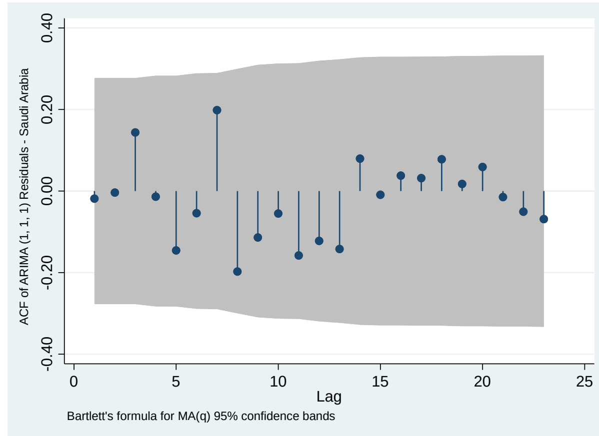

Figure 14. ACF of ARIMA(1, 1, 1) Residuals - Saudi Arabia

Source: Author's calculations

For Saudi Arabia, Figures 13 and 14 of PACF and ACF for the residuals are flat which indicates all information has been captured. So, the forecast will be based on this model **ARIMA (1, 1, 1).**

Residuals series of ARIMA (1, 1, 2) for Egypt and ARIMA (1, 1, 1) for Saudi Arabia (as shown in figures 11,14, and table 6, 7) respectively convey that the residuals are constant in mean and variance over time therefore proving their stationarity as a series.

5.4 Step Four: Forecasting

Since econometric forecasting is a series of both statistical and mathematical modelling, for predicting economic growth, it gives the chance for economists to analyze past economic trends and forecast new ones. Table Eight displays that the forecasting power of both the Egyptian and the Saudi models is relatively high, indicated by the minor difference between the actual and fitted values. The ten years ahead forecasts of Egypt and of Saudi Arabia is further presented below in Figures 17 and 18.

Table 8. Using fitted ARIMA Model to forecast GDPC

Year	**Forecasted GDPC – Egypt**		**Forecasted GDPC – Saudi Arabia**	
	Observed	**Predicted**	**Observed**	**Predicted**
2014	2648.29	2649.65	21087.35	21154.54
2015	2703.74	2679.60	21399.10	21292.61
2016	2761.39	2753.51	21270.47	21635.07
2017	2817.32	2818.45	20693.94	21406.04
2018	2907.32	2865.56	20775.20	20663.82
2019		2971.96		20837.18
2020		3036.52		20938.59
2021		3084.68		21069.36
2022		3127.58		21222.01
2023		3168.80		21390.94
2024		3209.47		21571.99
2025		3249.97		21762.07
2026		3290.41		21958.88

2027	3330.83	22160.69
2028	3371.25	22366.23
2029	3411.67	22574.54
2030	3452.09	22784.93

Source: Author's calculations

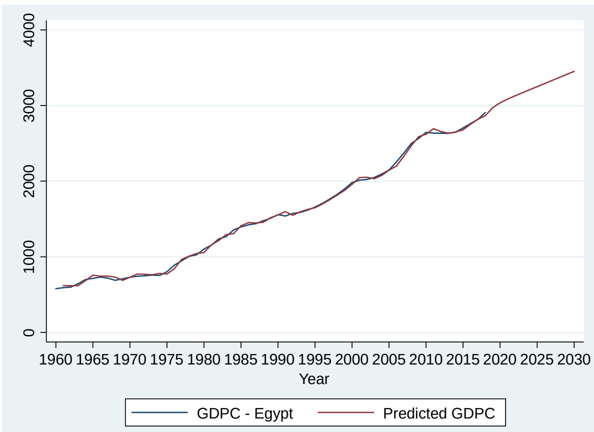

Figure 17. Time Series Plot for actual and predicted GDPC – Egypt

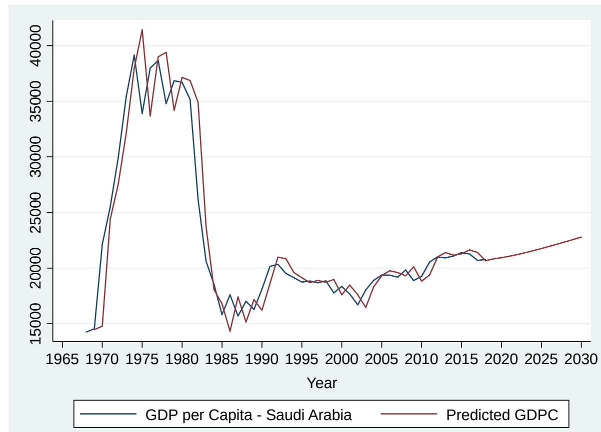

Figure 18. Time Series Plot for actual and predicted GDPC – Saudi Arabia

Source: Author's calculations

6. Discussion of Results

Notwithstanding the fact that the national economy is a complex, dynamic system, the results of the forecasted models can be fed into structural models and simulations to enrich the policy making process of Egypt and Saudi Arabia. Policy makers should work on maintaining the stability of the economy to prevent the economies from severe fluctuations.

According to the PwC's World in 2050 report, a second tier of emerging economies that have potential in significant growth will exist, into "pockets of opportunity" including Saudi Arabia and Egypt; this is due to an increase in two mutual forces of higher population growth and rising per capita GDP as suggested in the paper; this goes in parallel with the fulfillment of their policies and plans to ensure the implementation of the United Nations Sustainable Development Goals SDG and other conditionalities that could be discussed in further research. In lines with our graphs, the predictions will not be so smooth to achieve within the global boom and recessions, political and technological changes taking places. However, we could assume that potential growth will likely happen within the context of growth friendly policies if implemented, in accordance with the basics of economic theory to maximize the efficient use of factors of production and rely on the concept of resource scarcity and the urging need for economic diversification in both countries.

7. Conclusion

The purpose of this study is to model and forecast the Egyptian and Saudi Arabian GDP per capita using the Box Jenkins approach based on annual data (from 1960 to 2018) and (1968 to 2018). Box Jenkins four-staged approach is used to develop the best fit ARIMA model for the Egyptian and Saudi Arabian GDPC, in context with forecasting the countries' GDPC for the next five years. A series of testing processes were used; time series plots testing for stationarity of data, MLE testing for model estimations, AIC and BIC testing for goodness-of-fit measures, and different order autoregressive and moving average ARIMA models testing for the best fit model. Conclusions convey that the best fit model for Egypt is ARIMA (1,1,2) and for Saudi Arabia (1,1,1). The paper suggests the continuous growth in both Egyptian and Saudi Arabian GDPC, if certain criteria in real life is to be considered. As an experimental research, time-series modelling allows economists to be in charge of the situation in terms of identifying the cause and effect of relationships between variables, and therefore be able to find alternatives and methods for treatment. It is more of a base for further analysis in understanding the dynamics of GDP as a whole or any of the individual components in any country using different models. Modeling and forecasting GDP per capita could also be conducted using other methods and compared to the ARIMA model.

With the current situation and the emergence of the COVID-19 pandemic, Saudi-Russian oil price war further analysis and policy making research is required to link between the upcoming world recession and how these two countries will be able to set policies and implement them in order to reach their forecasted per capita GDPs. This paper sets a quantitative model for policy makers in Egypt and in Saudi Arabia as a guiding base towards progressing in terms of forecasted economic growth GDP per capita patterns. The significance is also evident in conducting further research by analyzing the implementation of policies in both countries towards the current global situation and their plans towards achieving and implementing the United Nations Sustainable Development Goals.

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Notes

Note 1. Source: theglobaleconomy.com with sources from the World Bank and IMF. Data are in constant 2010 U.S. dollars.

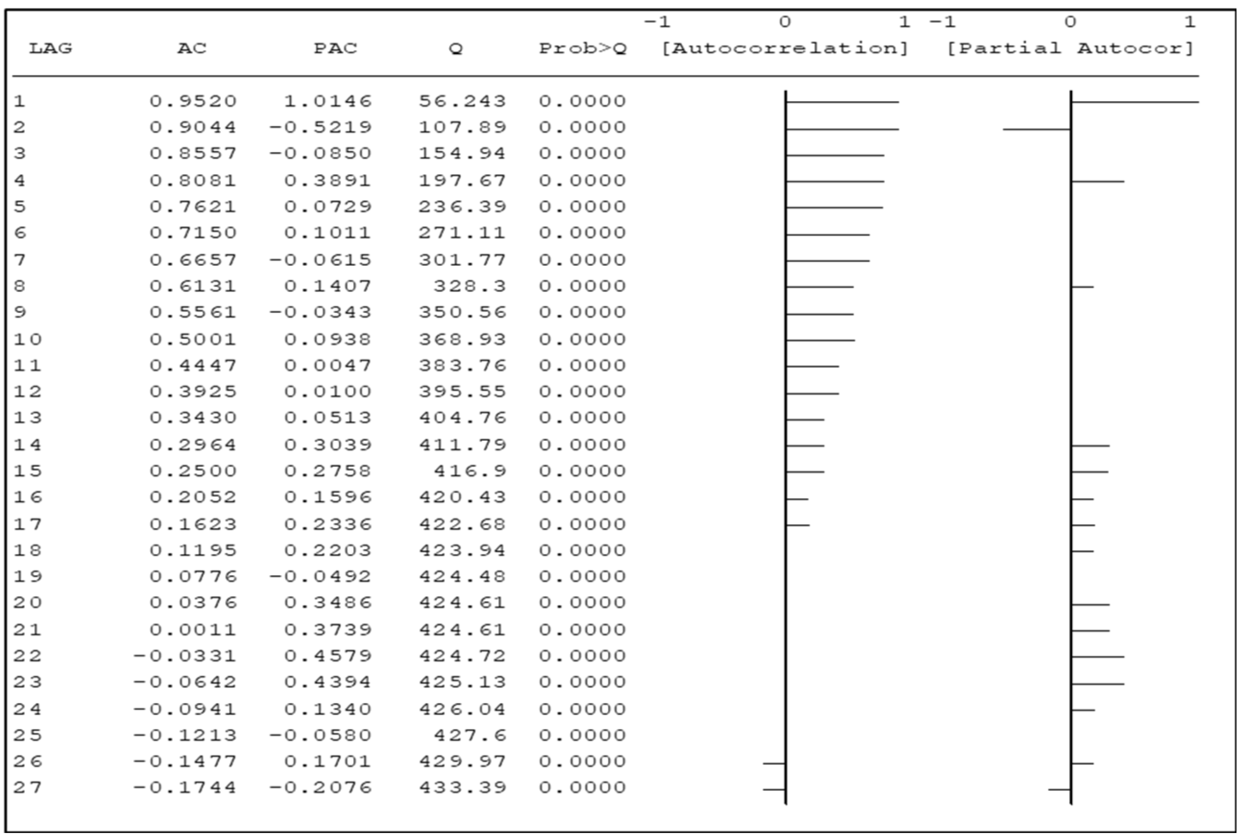
Note 2. Box and Jenkins (1976) named after statisticians George Box and Gwily Jenkins methodology is an integral part of calculating per capita GDP (Dritsaki, 2015).

Note 3. Constancy of the mean and variance overtime is an indicator of the stationarity of a time series model with a dependency of the value of the covariance on the distance between the two time periods rather than the actual time at which the variance is computed (Gujarati, 1995).

List of Abbreviations

Abbreviation	**Word**
ARIMA	Autoregressive-Integrated Moving Average
ACF plots	Autocorrelation Function Plot
ADF	Augmented Dickey and Fuller unit root test.
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BVECM	Bayesian Vector error correction model
GDP	Gross Domestic Product
GDPC	GDP per capita
MA	Moving average
PACF plots	Partial Autocorrelation Function Plot
SDG	Sustainable Development Goals
SETAR	Self-Exciting Threshold Auto Regressive models
VER	Vector Autoregression

Appendix



LAG	AC	PAC	Q	Prob>Q
1	0.9520	1.0146	56.243	0.0000
2	0.9044	-0.5219	107.89	0.0000
3	0.8557	-0.0850	154.94	0.0000
4	0.8081	0.3891	197.67	0.0000
5	0.7621	0.0729	236.39	0.0000
6	0.7150	0.1011	271.11	0.0000
7	0.6657	-0.0615	301.77	0.0000
8	0.6131	0.1407	328.3	0.0000
9	0.5561	-0.0343	350.56	0.0000
10	0.5001	0.0938	368.93	0.0000
11	0.4447	0.0047	383.76	0.0000
12	0.3925	0.0100	395.55	0.0000
13	0.3430	0.0513	404.76	0.0000
14	0.2964	0.3039	411.79	0.0000
15	0.2500	0.2758	416.9	0.0000
16	0.2052	0.1596	420.43	0.0000
17	0.1623	0.2336	422.68	0.0000
18	0.1195	0.2203	423.94	0.0000
19	0.0776	-0.0492	424.48	0.0000
20	0.0376	0.3486	424.61	0.0000
21	0.0011	0.3739	424.61	0.0000
22	-0.0331	0.4579	424.72	0.0000
23	-0.0642	0.4394	425.13	0.0000
24	-0.0941	0.1340	426.04	0.0000
25	-0.1213	-0.0580	427.6	0.0000
26	-0.1477	0.1701	429.97	0.0000
27	-0.1744	-0.2076	433.39	0.0000

Figure 19. ACF and PACF plots of GDPC - Egypt, 1968 – 2018

LAG	AC	PAC	Q	Prob>Q
1	0.9167	0.9176	45.425	0.0000
2	0.7904	-0.3568	79.887	0.0000
3	0.6565	-0.2206	104.16	0.0000
4	0.4986	-0.2756	118.46	0.0000
5	0.3440	-0.0972	125.41	0.0000
6	0.2169	-0.0030	128.24	0.0000
7	0.1096	-0.0927	128.98	0.0000
8	-0.0247	-0.2648	129.01	0.0000
9	-0.1150	0.1393	129.87	0.0000
10	-0.1732	-0.0560	131.84	0.0000
11	-0.2161	0.0408	135	0.0000
12	-0.2153	0.1490	138.21	0.0000
13	-0.1821	0.0029	140.57	0.0000
14	-0.1244	0.0097	141.7	0.0000
15	-0.0930	-0.0749	142.35	0.0000
16	-0.0749	-0.0550	142.78	0.0000
17	-0.0672	-0.0190	143.14	0.0000
18	-0.0729	-0.0512	143.58	0.0000
19	-0.0831	-0.0521	144.16	0.0000
20	-0.1054	-0.1024	145.13	0.0000
21	-0.1303	-0.1392	146.66	0.0000
22	-0.1568	-0.0494	148.95	0.0000
23	-0.1710	-0.0432	151.77	0.0000

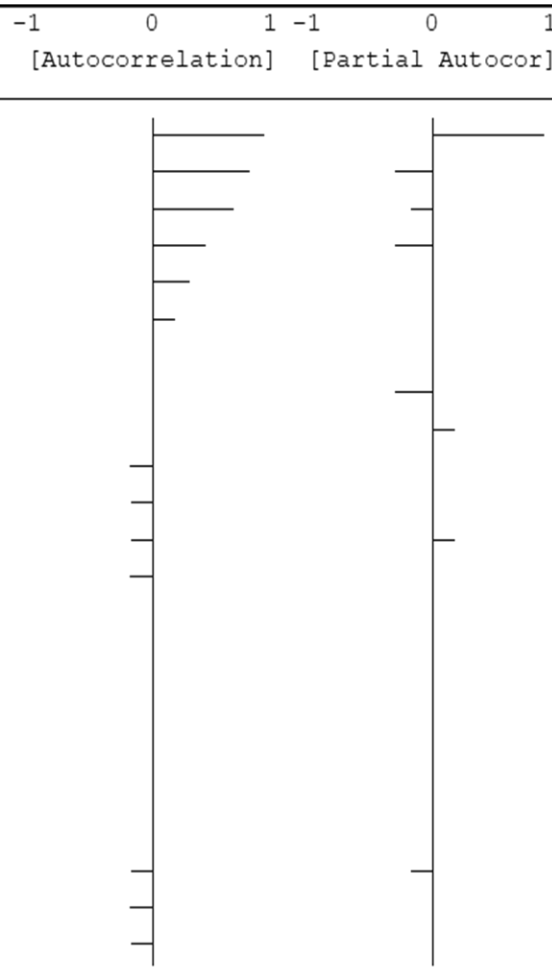


Figure 20. ACF and PACF plots of GDPC - Saudi Arabia, 1968 – 2018