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GDP Modelling and Forecasting using Arima: An Empirical Study for Cameroon

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Abstract

Gross domestic product (GDP) is a significant metric used to describe and assess economic activities and levels of growth. It's also regularly used by decision-makers to plot financial coverage. This paper's objective is to model and expect GDP in Cameroon. The current investigation employed the Box-Jenkins (JB) technique from 1980 to 2020. Based on the consequences, ARIMA (2, 1, 2) changed into discovered to be the optimal model for estimating GDP. The results of the desk-bound and identification guidelines time collection tests, as well as the use of aic and bic criteria, validated the outcomes, and an in-pattern forecast revealed that the relative and an in-pattern forecast, the relative and anticipated values were in the 5% area. This model's forecasting effectiveness is exceptional and efficient in modelling Cameroon's annual GDP.

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Introduction

Accurately estimating the gross domestic product (GDP) is a crucial approach to gaining insight into the overall direction of future economic activity, enabling the formulation of appropriate economic development strategies, allocation of funds based on various government priorities, and the implementation of effective economic policies. Parkin (2011) defines GDP as the total market value of all finished goods and services that are produced within a country's borders over a given time period, such as annually, semi-annually, or quarterly. This metric is widely recognized as a key indicator of a nation's economic growth and employment level. As a result, forecasting GDP values is an intriguing challenge for researchers and policymakers in the field of general economics, particularly in implementing economic development policies and norms (Dongdong, 2010). The significance of GDP is projected to rise in the future, particularly in Cameroon, due to extraordinary situations such as the ongoing global coronavirus pandemic that is projected to have a significant impact on the GDP of all nations. Consistent with the world financial institution, Cameroon is ranked 99th global and 16th in Africa, with a GDP of 38.5 billion greenbacks in 2020 and forty-five. 7 billion in 2022. The constant growth in its financial boom manner that Cameroon, a less evolved country, may want to drop out of its economic stature. Given new tendencies in Cameroon's GDP, economists need to be more conclusive about how long the fashion will be ultimate. Time series forecasting uses a model based on a methodology called the Car-Regressive-Included-Moving-Average (ARIMA) method, developed initially using Box and Jenkins (1976). This method has been modified based on the arena representation theorem. According to the arena representation theorem, any stationary time series contains infinite moving common point (MA) diagrams. This means that previous trends can be used to express its evolution (Jovanovic & Petrovska, 2010). The following is the remainder of the essay. Part 2 reviews the literature, part 3 describes the theoretical legacy, statistical analysis and empirical results, and sooner or later, part 4 concludes.

Literature review

Theoretical review

Various methodologies have been utilized in prior studies to forecast economic time series. An approach commonly used for univariate forecasting, also referred to as Box and Jenkins' method, is the Autoregressive Integrated Moving Average (ARIMA) model (Box and Jenkins, 1976). In this model, the autoregressive component of previous values and the present and lagged values of a white noise error term are used to define a time series (the moving average component). Many scholars have employed this method in their forecasting research due to its accuracy, provided that all the prerequisites for its application are met. For instance, Kenny and his colleagues (1998) utilized the ARIMA model to forecast Irish inflation by identifying the integrated degree, number of autoregressive terms, and number of moving average representations required in the time series used in models for forecasting Irish inflation. According to the research, the consumer price index's expected values match the actual values. Box and colleagues (1975): An ARIMA model of a given time series must be devoid of nonlinearity in order to be determined. However, the linearity assumption is rarely verified, especially for macroeconomic series. In practice, it is common for time series to be affected by outliers, missing data, calendar effects, working day effects, holiday effects, seasonality, change in diet, etc. To appropriately model the time series affected by such products, mainly using

ARIMA models, it is necessary to eliminate these effects, interpolate the missing data, correct the aberrant data, and carry out any other prior treatment allowing their linearization.

Empirical review

Box and Jenkins's (1976) method has been used substantially using many researchers to focus on the destiny charges of gross domestic product (GDP). In their study, Wei et al. (2010) utilized GDP data from Shaanxi spanning from 1952 to 2007 to predict the GDP of the United States for the next six years. Making use of the Arima (1, 2, 1) version, they found that the GDP of Shaanxi affords an excellent growing fashion. Marty and Cha (2012) examine the forecasting of the GDP boom charge for India over a 60-year period using the Arima (1, 2, 2) model. The consequences of their observation confirmed that anticipated values comply with an increasing fashion for the coming years. Zhang Haonan (2013) examines GDP projections for his five regions of Sweden from 1993 to 2009 using his three modes of Arima, Var and Ar(1). The consequences of the test showed that all 3 fashions could be used for short-term forecasting. However, the primary-order autoregressive version is better suited to predict inline her per capita GDP for her five areas in Sweden. Shahini and Harder (2013) investigate Albanian GDP projections using quarterly data from 2003 to the second quarter of 2013. They employed the organization's ARIMA and VAR versions to make their estimates. Their findings revealed that the group VAR version outperformed the ARIMA model in terms of GDP forecasts. Zakai (2014) investigates Pakistan's GDP predictions using quarterly data from 1953 to 2012. To assess the magnitude of the Pakistan GDP boom from 2013 to 2025, use the ARIMA (1, 1, 0) model. Additionally, yang et al. (2016, December) used the ARIMA (2, 2, 2) model to forecast the Chinese GDP. The results demonstrated that this version effectively estimates GDP in the short run. Wabomba et al. (2016) used data from Kenya's national bureau of statistics from 1960 to 2012 to create their model. ARIMA models were used to forecast Kenyan GDP. An in-sample prediction revealed that the relative and forecasted values were within 5% of the true values, indicating that the forecasting capacity of this model has become pretty acceptable and green in modelling the yearly returns of Kenyan GDP in the future. Uwimana et al. (2018) used the ARIMA model to anticipate future time series values in twenty of Africa's largest economies. Based on the estimates, the research concluded that GDP growth would increase from 1990 to 2030, with Africa's average rate of growth estimated to be 5.52%. Agrawal (2018) used ARIMA and publicly accessible quarterly real GDP data from 1996 quarter 2 to 2017 quarter 2 to model and estimate real GDP in India. The results demonstrate that each forecast appears to be convergent. From 1965 to 2016, Abonazel and Abd-elftah examined Egyptian GDP and the use of annual statistics from the World Bank. ARIMA (1, 2, 1) was the best variant based on minimal AIC, BIC, and MSE to forecast the GDP of the United States of America from 2017 to 2026. Their findings revealed that Egypt's GDP would rise on a regular basis. Salah and Tanzim used Arima (1, 2, 1) to forecast Bangladesh's GDP from 2019 to 2025. Their analysis indicated that Bangladesh's GDP trend is improving gradually. Chikumbe and Sikota evaluated Zambia's GDP from 1960 to 2018 using annual data. The ARIMA (5, 2, 0) version altered when using the Field-Jenkins method since the best form of projecting Zambia's GDP is based on the minimum AIC and BIC. The version was used to forecast for the next 8 (eight) years, and the results suggested that the DGP trend may fall between 2020 and 2022. Touama examined Jordan's GDP data from 2003 to 2013 using the ARIMA method. The results revealed that the Arima (0, 1, 2) model is the appropriate version for forecasting Jordanian GDP. Wabomba et al. (2016) used the ARIMA technique to estimate Kenyan GDP from 1960 to 2012. Their findings established the ARIMA (2, 2, 2) model as the best model for forecasting future GDP. Arneja et al (2018). they examined India's GDP using annual data from 1980 to 2017, and an Arima (1, 1, 7) derived as the best model was used to anticipate the Indian GDP; their findings suggested that India's GDP could rise recklessly in the future. Miah et al. the GDP of Bangladesh was tested using statistics ranging from 1960 to 2017, using the Arima procedure; the final results confirmed that the Arima (1, 2, 1) version is the nice version for forecasting the Bangladesh GDP; the model was used in forecasting for the following 13 years, and the GDP of Bangladesh is expected to improve during the forecast. Awel used annual numbers from 1981 to 2014 to conduct an analysis of Ethiopia's actual GDP. The Arima (1, 1, 1) model was chosen as the best prediction version, and it was used to forecast from 2015 to 2017. Rana tested the Arima forecast version utilising monthly data spanning from July 2016 to July 2018, employing the container-Jenkins approach to select Arima (0,1,2) as the exceptional version to forecast Nepal's GDP.

Methodology

Data source

To forecast GDP growth, data on this macroeconomic variable were collected from the the World Bank and World Development Indicators (WDI) from 1980 to 2020. It is a single collection of data for modelling that includes annual GDP growth rates for Cameroon. The data set contains 37 observations.

Specification Model

According to Granger and Newbold (1986), time series analysis can provide highly accurate and efficient forecasts when sufficient data on relevant variables are available. The Arima model is a broadly employed and flexible approach for univariate time series analysis. It combines three techniques: (1) autoregressive (AR) modeling, (2) differencing, and (3) moving average (MA) modeling. These methods are considered fundamental models for univariate time series in the statistical literature and are widely utilized in numerous applications.

Autoregressive (Ar) model

The autoregressive model Ar (p) of order p can be written as follows:

$$X_t = c + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_P X_{t-P} + \mu_t \quad ; \qquad t = 1, 2, \ldots t \tag{1}$$

Here, μ_t is the error term within the equation; where μ_t a white noise system, a sequence of independently and identically distributed (IID) random variables with $E(\mu_t \quad) = 0$ and $var(\mu_t \quad)$ = σ 2; i.e., $\mu,_t \sim IID\ N(0, \sigma^2)$. This model includes all previous values of X_t in order and can have long-term effects, making it a memory model.

Moving-average (Ma) model

A time-series $\{X_t\}$ is stated to be a moving-average procedure of order q, Ma (q), if:

$$X_t = \mu_t - \varphi_1 \mu_{t-1} - \varphi_2 \mu_{t-2} - \cdots - \varphi_q \mu_{t-q} \tag{2}$$

This version is given as explanatory variables in terms of prior mistakes.

As a result, best-q mistakes will have an influence. $However$, best-order errors do not impact X_t, meaning it is a short-memory model.

Autoregressive moving average (ARMA) model

A time-series $\{X_t\}$ is stated to observe an autoregressive moving-average process of order p and q, ARMA (p, q), the method if:

$$X_t = c + \beta_1 X_{t-1} + \cdots + \beta_P X_{t-P} + \mu_t - \phi_1 \mu_{t-1} - \cdots - \varphi_q \mu_{t-q} \quad (3)$$

ARIMA Models

By introducing data series differencing, ARMA models can be extended to nonstationary series, leading to the development of ARIMA models. The general non-seasonal ARIMA model is denoted by Arima (p, d, q), where p represents the autoregressive order, d denotes the degree of differencing, and q stands for the moving average order. For instance, if X_t is a nonstationary series, we can obtain a first-difference of X_t, so that ΔX_t becomes stationary. Then, the Arima (p, 1, q) model can be used to model the stationary time series.

$$\Delta X_t = c + \beta_1 \Delta X_{t-1} + \cdots + \beta_P \Delta X_{t-P} + \mu_t - \varphi_1 \mu_{t-1} - \cdots - \varphi_q \mu_{t-q} \quad (3)$$

Where $\Delta X_t = X_t - X_{t-1}$. Nevertheless, if $p = q = 0$ in equation (4), the model becomes a random walk model, classified as $Arima\ (0, 1, 0)$.

Box-Jenkins Approach

The Box-Jenkins approach was developed by statisticians George Box and Gwilym Jenkins in 1970. This method uses Arima models to determine the best fit for a time series model beyond the values of a time collection in time series analysis. Further information on Box-Jenkins time series analysis can be found in Frain (1992), Kirchgässner et al. (2013), and Chatfield (2014). Figure 1 shows the four iterative stages of modeling used in this approach.

Model identification: Identifying a model involves ensuring that the variables are stationary, detecting any seasonal patterns within the collection, and utilizing plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series to determine which model component to use, whether it is the autoregressive or moving average.

Model estimation: The chosen ARIMA model's coefficients are computed using a computational algorithm. The most commonly used methodologies for this purpose are maximum likelihood estimate (MLE) or nonlinear least-squares estimation. These methods aim to find coefficients that best fit the ARIMA model.

Model-checking: After estimating the model, it is necessary to verify if the conditions for a stationary univariate process are met. Specifically, the residuals should be independent and have a constant mean and variance over time. The ACF and PACF of the residuals can be used to identify any specification issues. If the estimation is inaccurate, it is necessary to go back to step 1 and develop a better model. Moreover, to select the best model for the data, the estimated model should be compared to several ARIMA models. Two general criteria are used for model selection, namely, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC).

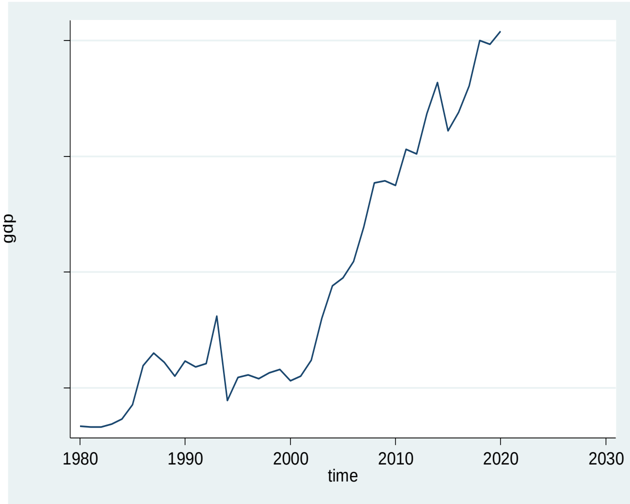
$$AIC = 2m - 2\ln(\hat{L}), \qquad BIC = \ln(n)\, m - 2\ln(\hat{L}), \quad (5)$$

In the formula ($\hat{L}$), the maximum value of the probability function of a given model is determined based on the number of parameters (m) and the sample size (n). The traditional criteria of mean squared error (MSE) are commonly employed to compute Fast AIC and BIC. If the parameters of an ARIMA model satisfy the requirements of a stationary univariate process, the model can be utilized for forecasting purposes.

Empirical Analysis and Results

For our study, we focused solely on the GDP (constant 2010 US dollars) variable. We plotted its values over the time period spanning 1980 to 2020, as illustrated in figure 1. We obtained the data from the World Development Bank (WDI) database. To analyze the data, we employed the Arima technique, which involves a four-step process of ensuring stationarity, identifying the model, estimating its parameters, and conducting hypothesis tests. This process is iterative.

Figure 1: the trend of Cameroon GDP (1980-2020)



Testing for Stationarity

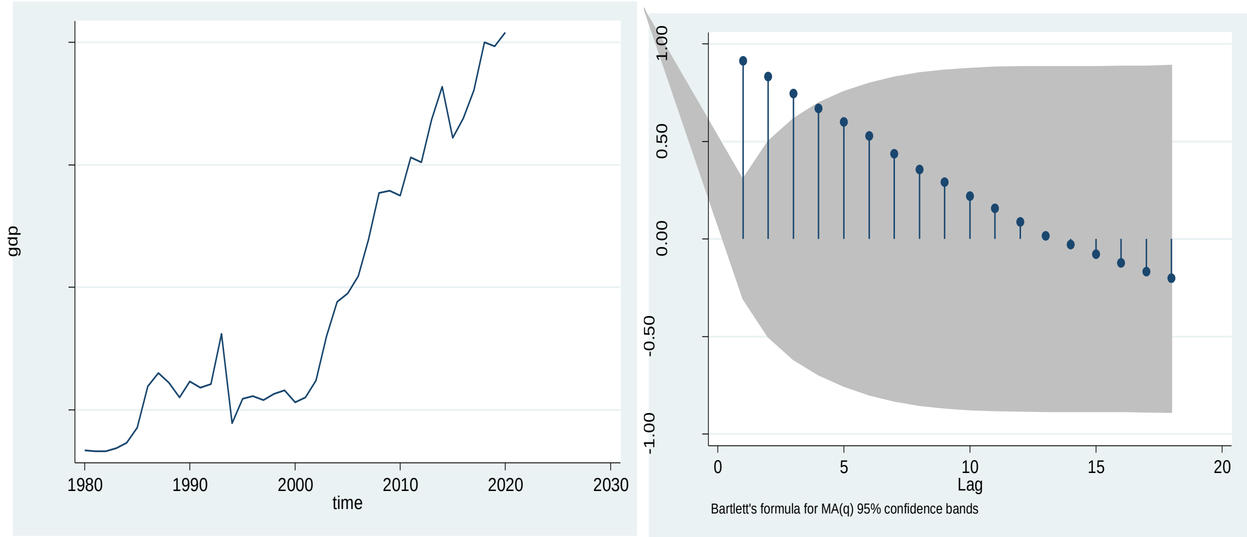
Table 1: Unit Root Tests

Test	variable	Test 1%level	critical 5%level	values 10%level	Statistic test	decision
	gdp	-4.242	-3.540	-3.204	-1.559 non	stationary
ADF	$d.gdp$	-3.655	-2.961	-2.613	-7.294	stationary
	gdp	-4.242	-3.540	-3.204	-1.388 non-	stationary
pp	$d.gdp$	-3.655	-2.961	-2.613	-7.355	stationary

Source: author calculation from Stata software

Table 1 displays the outcomes of the Phillip-Perron's (PP) and Augmented Dickey-Fuller (ADF) tests. The results reveal that our variables were non-stationary at their initial levels. However, the first difference renders them stationary at significance levels of 1%, 5%, and 10%. Once we obtain the fixed sequence, the subsequent step is to identify the appropriate model. To accomplish this, we utilize the H. Arima (p, d, q) approach to set the model parameters p and q. By examining the correlogram of the stationary series (gdp), we can determine the value of p by looking at the delay at which the Partial Autocorrelation Function (PACF) tapers off, and the value of q by looking at the delay at which the Autocorrelation Function (ACF) tapers off, as per Anderson (1976) and Box et al. (2015). Additionally, since the model is stationary after the initial differencing, we set d=1.

Figure 2: Correlogram representing the real GDP growth rate series of Cameroon at the level



The figure above presents the re-estimated Partial Autocorrelation Function (PACF) of the difference series. As evident from the plot, there is a significant peak at lag 3. This observation leads us to accept the null hypothesis that the series of precise GDP rates across the 40 observations is not stationary. Given that the Autocorrelation Function (ACF) and PACF exhibit peaks at lag 3, we can utilize the difference in this model. Figure 3 depicts that the time series appears to be stationary after applying first-order differencing (i.e., computing the period-to-period change). Notably, there is no discernible upward or downward trend. This information can be leveraged to construct an Arima (p, d, q) model.

Table 3: First-order difference of GDP growth in Cameroon (1980-2020)

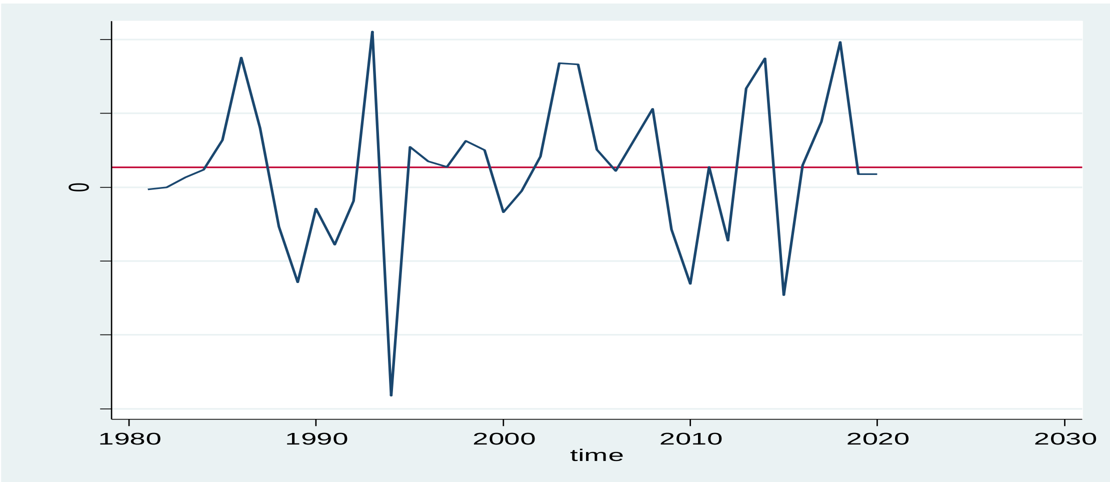
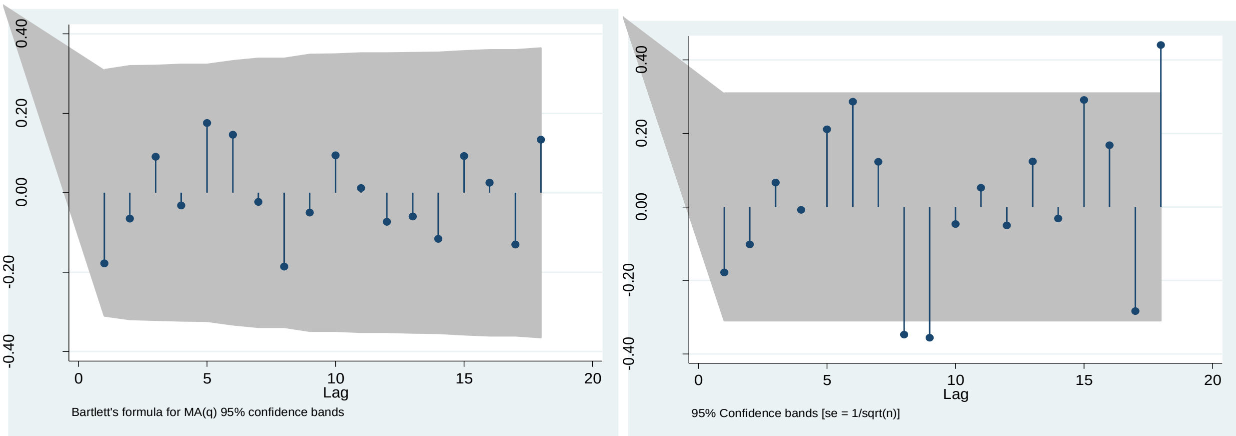


Figure 4: Correlogram of Cameroon real GDP rate series (First Differences)



As shown in Figure 4, there are no significant spikes in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the initial difference series at any lags. Consequently, our time series is now stationary, and for time series, ARIMA models with initial differences are preferred. The residuals obtained from the ACF and PACF of the first differencing indicate that the GDP growth series is free from any residual issues.

Estimation of the model

As the BJ methodology is intended for stationary time series, it is essential to transform the nonstationary series into a stationary one before modeling. Once we identify the appropriate values for p and q, we will use appropriate estimation techniques to evaluate the parameters of the temporary ARIMA model we have selected.

Table 2: Evaluation of ARMA models (with a constant)

	Models			Best Model
	ARIMA(1,1,1)	ARIMA(2,1,2)	ARIMA(3,1,1)	
Coef of AR and MA	2	3	2	ARIMA(2,1,2)
Sigma(volatility)	2.10e+09	2.02e+09	2.15e+09	ARIMA(2,1,2)
Lag-likelihood	-917.71275	-915.04469	-916.5625	ARIMA(2,1,2)
AIC	1841.426	1840.089	1843.125	ARIMA(2,1,2)
BIC	1849.492	1848.534	1851.569	ARIMA(2,1,2)

According to the data presented in Table 2, the model with the lowest values of AIC, BIC, and volatility outperforms the model with the highest values of AIC, BIC, and volatility (Nyoni, 2018). In this study, we will employ AIC to identify the best model for modeling and forecasting the GDP rate of Cameroon. Accordingly, we have selected the ARIMA (2,1,2) model.

Table 3: OLS results of ARIMA (2, 1, 2) model

Type (GDP)	ARIMA model
Constant	8.776008 (0.005)***
AR	
L1	0.968455 (5.72)***
L2	-0.7133073 (-4.50)***

MA	
L1	-1.33947 (-5.75)**
L2	0.999964 (3.15)***

Significance at the 1%, 5%, and 10% are indicated by ***, **, *respectively
The results in table 3 above show that both coefficients are statistically significant at a 1% significance level.

Diagnostic of the model

We can assess the goodness of fit of the selected model by examining the correlogram of the estimated residuals. If the estimated residuals exhibit white noise characteristics, we can accept the chosen model; otherwise, we may specify a new ARIMA model starting from stage 'a'. Therefore, the BJ technique is an iterative process, and these three stages will be repeated until an acceptable ARIMA model is obtained.

Table 4: Portmant test

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Portmanteau test for white noise

 Portmanteau (Q) statistic =    10.2753
 Prob > chi2(18)           =     0.9225
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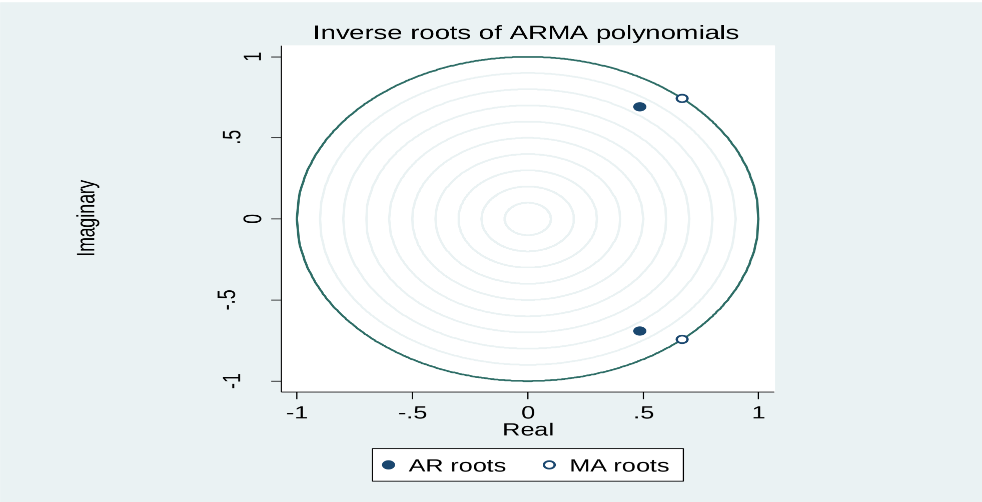
Take a look at this table: pp>0.05. Because we cannot rule out the null hypothesis, we can conclude that the residuals are white noise.

Figure 5: Inverse Roots of AR and MA



The selected ARMA (2, 1, 2) model is considered stable as the inverse roots of its characteristic polynomial are inside the unit circle. Furthermore, the residuals of the model show white noise characteristics. Therefore, this model is appropriate for modeling and forecasting the GDP of Cameroon.

Forecasting ARIMA model

We have chosen the ARIMA (2, 1, 2) model as the most suitable one to forecast the GDP of Cameroon in our study. The predictions for the GDP of Cameroon from 2020 to 2030 using the ARIMA (2, 1, 2) model are presented in Table 6 below:

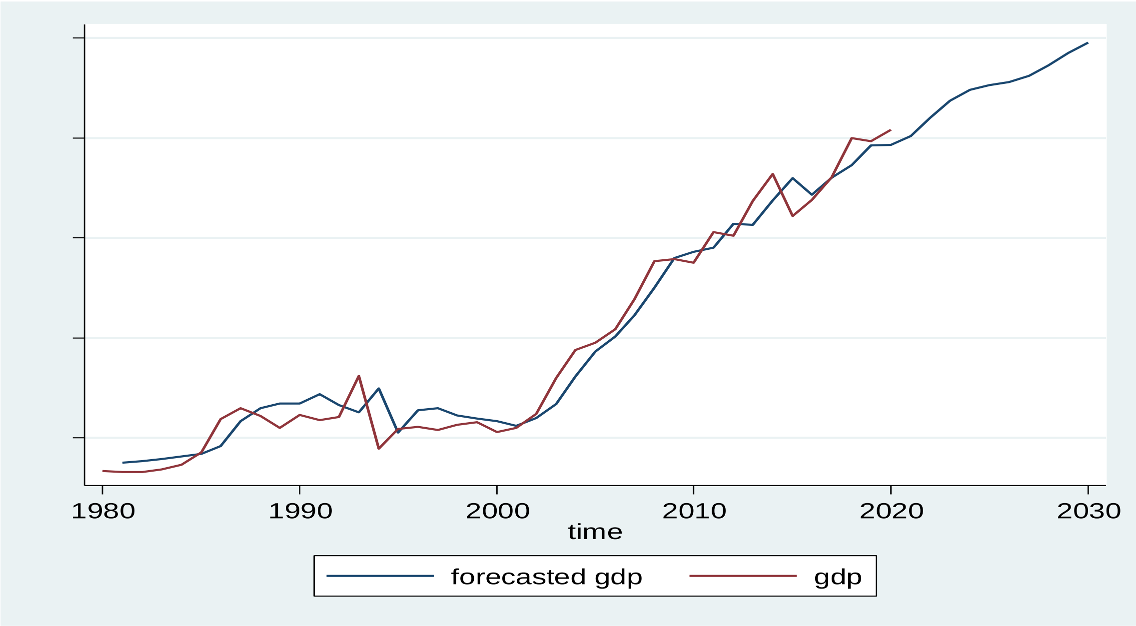
Table 5: Projected Growth rate for the subsequent ten years using ARIMA (2,1,2)

Years	Projected Growth rate
2021	4.02
2022	4.20
2023	4.38
2024	4.48
2025	4.53
2026	4.56
2027	4.62
2028	4.73
2029	4.85
2030	4.96

Source: compiled from data

The table presented above displays a steady rise in the GDP rate over the forecast period. Furthermore, Figure 6 compares the predicted and actual values and indicates a close match between them. Based on this, we can conclude that the ARIMA (2,1,2) model fits the data well.

Figure 6: GDP growth forecasting



Conclusion

The aim of this study was to utilize annual data from 1980 to 2020 to model and predict the GDP of Cameroon using the Box-Jenkins methodology. The Box-Jenkins method was implemented in four stages to obtain a suitable Arima model for the GDP of Cameroon. Time series and correlograms were employed to check the stationarity of the data. The maximum likelihood estimation was adjusted to infer the version. Various Arima models were compared using different measures of goodness of fit (MSE, AIC, and BIC), as well as with different orders of autoregression and transfer function. The appropriate Arima (p, d, q) model was identified, with the optimal p and q determined using the corresponding correlogram. The Arima (2,1,2) model was found to be the best fit for the dataset. Furthermore, the results suggested that the GDP rate in Cameroon is projected to continue increasing over the next ten years.

Reference

Agrawal, V. (2018). GDP Modeling and forecasting using ARIMA: an empirical study from India. Doctoral dissertation, Central European University.

Anderson, O. (1976). Time Series Analysis and Forecasting. London: Butterworths

Augmented, D. F. T., (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427–431. The European System of Accounts ESA 1995, Eurostat, 1996.

Branimir, J. & Magdalena, P. (2010). Forecasting Macedonian GDP: Evaluation of different models for short-term forecasting. Working Paper, National Bank of the Republic of Macedonia.

Chaido, D., (2015). Forecasting real GDP rate through econometric models: An empirical study from Greece, Journal of International Business and Economics, 3, 13–19. https://doi.org/10.15640/jibe.v3n1a2

Charline, U., & al (2015). Forecasting Inflation in Kenya Using Arima-Garch Models. International Journal of Management and Commerce Innovations, 3, 15–27.

Christ, C., (2016). The Analysis of Time Series: An Introduction. CRC Press.

Clive, W. P. G., (1986). Newbold, Forecasting Economic Time Series, Academic Press.

Gebhard, K., & all al13). Univariate Stationary Processes, in Introduction to Modern Time Series Analysis, Springer, Berlin, Heidelberg, 27-93. https://doi.org/10.1007/978-3-642-33436-8_2

George, E. B., & all. (2015). Time series analysis: forecasting and control. John Wiley & Sons.

George, E. P. B. , & Gwilym, M. J. (1976). Time Series Analysis: forecasting and control. San Francisco: Holden-Day, Cambridge.

George, E. P. B. , & Gwilym, M. J. (1976). Time series analysis. Forecasting and control. Holden Day, San Francisco.

Hulya, S. & all2014. Explanation Of The Turkish Inflation Rate With Fisheries Export And Import. Journal of Academic Documents for Fisheries and Aquaculture, 1.

James, H. S. & Mark, W. W. (1999). Forecasting inflation. Journal of Monetary Economics, 44, 293-335.

James, H. S. & Mark, W. W. (2001). Forecasting output and inflation: the role of asset prices. National Bureau of Economic Research.

Jarque, C. M., & Bera, A. K., (1980). Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals, Economics Letters, 6, 255-259. https://doi.org/10.1016/0165-1765(80)90024-5

Jarque, C. M.,& Bera A. K.(1980). Efficient tests for normality, homoscedasticity, and serial independence of regression residuals. Economics Letters6(3), 255–259.

Kenneth, D. W. Forecast Evaluation. In G. Elliott, & all, Handbook of Economic Forecasting. Netherlands: Elsevier. 2006; 99-134.

Kenneth, F. W., (1974). Seasonal adjustment and relations between variables. Journal of the American Statistical Association, 69, 18-31.

Michael, A., & Massimiliano, M. Fiscal forecasting: The IMF, OECD, and EC track record. Econometrics Journal. 2001; 4(1), s20-s36.

Mohamed, R. A. & Ahmed Ibrahim, A. E.. (2019). Forecasting Egyptian GDP Using ARIMA Models. Reports on Economics and Finance, 5(1), 35-47.

Peter, M. S., & Alexander, P. 2009. Forecasting container transhipment in Germany. Applied Economics, 41, 2809-2815.

Robert, H.S., & David, S. S. (2006). Time series regression and exploratory data analysis. Time Series Analysis and Its Applications: With R Examples, 48-83.

Ruey, S. T. (2005). Analysis of financial time series, John Wiley & Sons.

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