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Original Article

Modelling and Forecasting Somalia GDP Using Autoregressive Integrated Moving Average (ARIMA) Models

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ABSTRACT

The Gross Domestic Product (GDP) is the total worth of all goods and services produced within a country's borders in a given year. The background of the study includes the importance of GDP as an important economic indicator reflecting the overall economic performance and growth of a country. As Somalia faces unique economic challenges, this research aims to provide insight into its GDP dynamics, trends, and potential future developments. In order to create the suitable Autoregressive-Integrated Moving-Average (ARIMA) model for the GDP data for Somalia, the Box-Jenkins method was used in this study. Data on the annual GDP of Somalia from 1972 through 2022 was taken from the Macrotrends database. ARIMA (3, 1, 8) was identified as the most suitable statistical model for the GDP of Somalia. The forecast for Somalia's GDP over the next five years was generated using this fitted ARIMA model. The findings indicated that a positive increase in Somalia's GDP over the next five years is expected. These forecasts line up with the historical trends and statistical correlations found by the ARIMA model.

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INTRODUCTION

In developing economies, Gross Domestic Product (GDP) is widely accepted as a key indicator for measuring a country's economic performance. GDP represents the total value of all goods and services produced within a country's borders in a given year (Osberg & Sharpe, 2002). This important economic measure is utilised by governments, investors, and analysts to gain insights into a country's economic health, growth trends, and future economic directions.

Somalia, located in the eastern part of the African continent, is a country with the potential for a robust economy due to its abundant natural resources. However, due to various internal and external challenges, its economic stability and growth can be subject to fluctuations. Therefore, understanding Somalia's economic performance and predicting future GDP trends are of vital importance for shaping economic policies and guiding investment decisions. In this study, Autoregressive Integrated Moving Average (ARIMA) models were employed to analyse and forecast Somalia's GDP. ARIMA models are widely used statistical methods for identifying current trends, irregularities, and cycles in time series data. By constructing an appropriate ARIMA model using the Box-Jenkins method, the aim of the study was to generate GDP forecasts for Somalia, considering historical trends and relationships in Somalia's GDP data.

LITERATURE REVIEW

Kiriakidis and Kargas (2013) conducted a comprehensive analysis of the Greek GDP and its determinants. The study identified key indicators, including the retail trade index, industrial production index, unemployment rate, and touristic index, that significantly influence the Greek economy. Furthermore, their forecasting models successfully predicted a high recession for the year 2012. The research emphasises the importance of considering multiple economic indicators and utilising forecasting models to understand and forecast GDP performance accurately.

In the study by Zhang and Rudholm (2013), three models, namely ARIMA, VAR, and AR (1), were used to analyse the forecasting of per capita GDP for five regions of Sweden between 1993 and 2009. All three models were found to be suitable for short-term forecasting. However, it was concluded that the autoregressive first-order model (AR (1)) performed most effectively in predicting the per capita GDP for the five regions of Sweden.

In their study, Shahini and Haderi (2013) examined the GDP forecast for Albania using quarterly data from the first quarter of 2003 to the second quarter of 2013. They used two sets of models, ARIMA and VAR, for the prediction task. The findings of their research showed that the group of VAR models outperformed the ARIMA model when it comes to forecasting GDP. This shows that the VAR models provide more accurate estimates of GDP in Albania compared to the ARIMA model.

Wabomb et al. (2016) used data from the Kenya National Bureau of Statistics dating from 1960 to 2012. The aim was to model and estimate Kenya's GDP using ARIMA models. Findings of within-sample estimates showed that the estimated values and actual values were relatively close and fell in the 5% range. This proved that the ARIMA model exhibits satisfactory predictive capabilities and is effective in modelling the annual returns of Kenya's GDP for future periods. Agrawal (2018) conducted a study to model and forecast the real GDP in India using ARIMA. The study utilised publicly available quarterly real GDP data from the second quarter of 1996 to the second quarter of 2017. The results of the analysis indicated that all the forecasts appeared to converge in the long run.

In the study by Abonazel and Abd-Elftah (2019), the appropriate statistical model for forecasting the Egyptian GDP was identified as ARIMA (1, 2, 1). This model was employed to forecast the GDP of Egypt until 2026. The forecasted values suggested that the GDP is expected to continue rising.

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Ghazo (2021) applied the Box-Jenkins methodology to forecast GDP and CPI in Jordan. The study identified ARIMA (3,1,1) as the best model for GDP and ARIMA (1,1,0) for CPI. The forecasts indicated a stagflation scenario in 2020, followed by a subsequent increase in both GDP and CPI.

MATERIALS AND METHODS

Time series analysis offers accurate short-term forecasts for variables of interest, particularly when applied to large datasets. Granger and Newbold (2014) have demonstrated the effectiveness of this approach. In the realm of univariate time series analysis, one widely utilised and flexible model is ARIMA. The ARIMA model comprises three distinct processes: the autoregressive (AR) process, the differencing process, and the moving-average (MA) process. These processes are well-established in statistical literature as the primary models for analysing univariate time series data and finding extensive applications across various domains. To avoid plagiarism, it is crucial to properly reference and attribute any direct quotes or specific ideas to their original sources.

Autoregressive (AR) Model

An autoregressive model of order p, AR(p), can be expressed as:

$$X_t = c + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t;\ t = 1,2, \ldots T \qquad (1)$$

Where ε_t is the error term in the equation; where ε_t a white noise process, a sequence of independently and identically distributed (iid) random variables with $E(\varepsilon_t) = 0$ and var $(\varepsilon_t) = \sigma^2$; i.e., $\varepsilon_t \sim$ iid $N(0, \sigma^2)$. In this model, all previous values can have additive effects on this level, X_t and so on; so, it is a long-term memory model.

Moving-Average (MA) Model

A time series $\{X_t\}$ is said to be a moving-average process of order q, MA (q), if:

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \qquad (2)$$

This model is expressed in terms of past errors as explanatory variables. Therefore, only q errors will effect onX_t, however, higher order errors do not effect on X_t; this means that it is a short-memory model.

Autoregressive Moving-Average (ARMA) Model

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

$$X_t = c + \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \qquad (3)$$

This model can be a mixture of both the AR and MA models above.

ARIMA Models

The ARMA models can be expanded to handle non-stationary series by introducing the concept of differencing, resulting in ARIMA models. The general form of the non-seasonal ARIMA model is represented as ARIMA (p, d, q), where p represents the autoregressive order, d indicates the degree of differencing, and q represents the moving-average order. To illustrate, suppose we have a non-stationary series called X_t. To make it stationary, we can take the first difference of X_t, denoted as ΔX_t. In this case, the appropriate model to use would be ARIMA (p, 1, q).

$$\Delta X_t = c + \alpha_1 \Delta X_{t-1} + \cdots + \alpha_p \Delta X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \qquad (4)$$

where $\Delta X_t = X_t - X_{t-1}$. But if $p = q = 0$ in equation (4), then the model becomes a random walk model, which is classified as ARIMA(0,1,0).

Box-Jenkins Approach

In time series analysis, the Box-Jenkins (1970) approach, named after the statisticians George Box and Gwilym Jenkins, applies ARIMA models to find the best fit of a time series model to past values of a time series. For more details about

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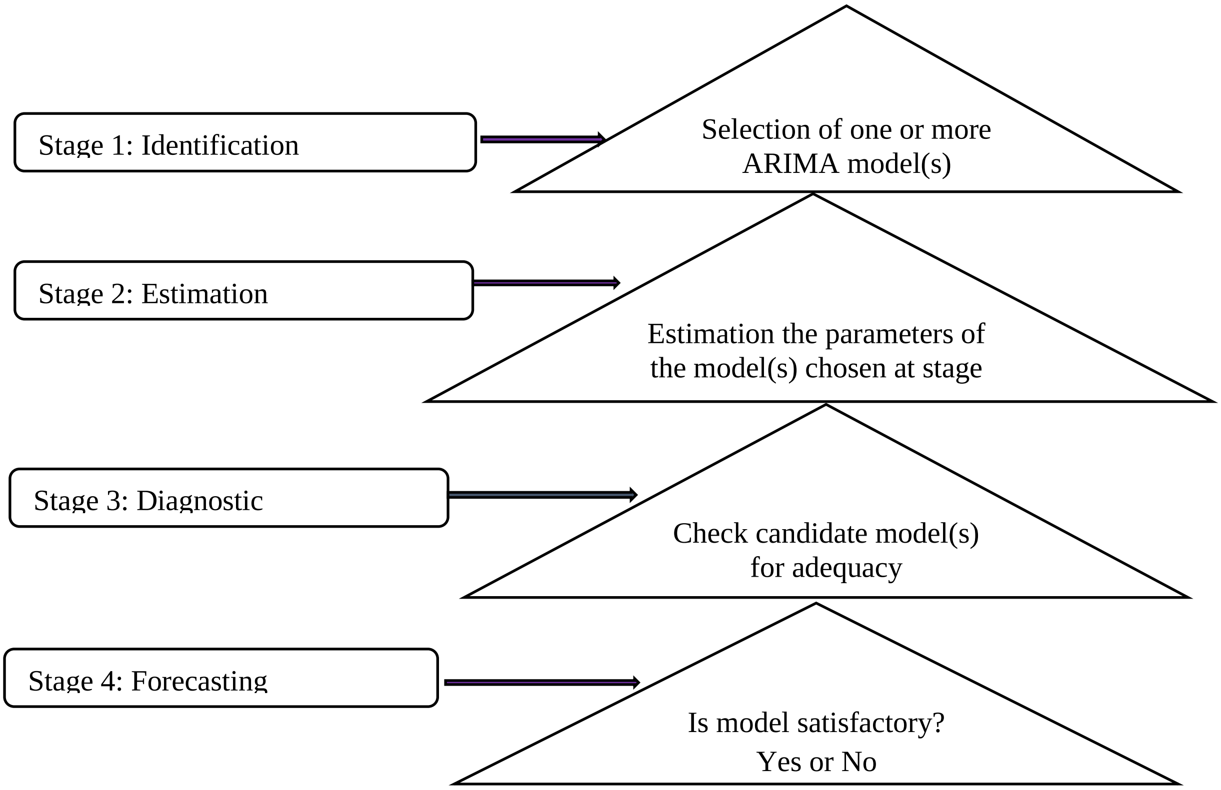
Box–Jenkins time series analysis, see for example, Young (1977), Frain (1992), Kirchgässner et al (2013), and Chatfield (2019).

Figure 1: Stages of modelling according to the Box-Jenkins approach



RESULTS AND DISCUSSION

In this study, the annual GDP of Somalia was obtained from the Macrotrends database from 1972 to 2022. This means that we have 51 observations of GDP, which satisfies the rule of having over 50 observations in the Box-Jenkins approach of your time series forecasting (Chatfield, 2016). Based on this data, we will propose the appropriate ARIMA model and then use it to forecast Somalia's GDP for the next five years (from 2023 to 2027).

Identification of the Model

Based on the ADF unit root test results, the p-value for the test statistic is reported as 0.9830. Since the p-value is greater than the commonly used significance level of 0.05, it further supports the conclusion that the null hypothesis of a unit root cannot be rejected. So, the Somalia GDP data at its original level is non-stationary, meaning it exhibits a trend or has a stochastic component that makes it difficult to model using traditional time series techniques. Further analysis and appropriate transformations or differencing methods may be required to achieve stationarity in order to apply appropriate time series models.

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Figure 2: Time series plot for Somalia GDP data

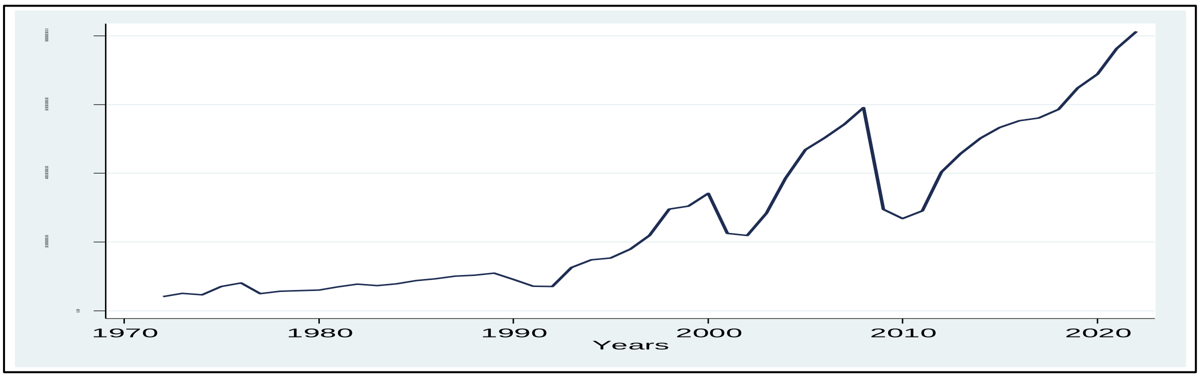
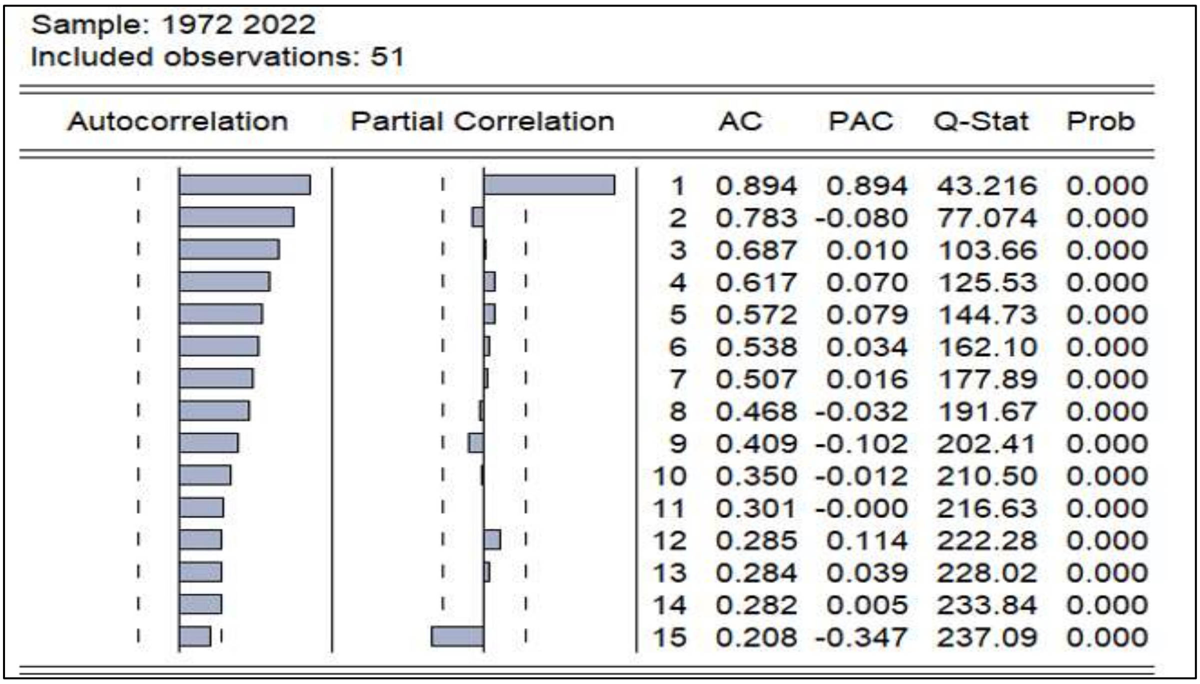


Table 1: Results of ADF Unit Root Test (Original Level) for Somalia GDP data

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Z(t)	0.442	3.580	--2.930	-2.600	0.9830

Figure 3: ACF and PACF plots for Somalia GDP data


Sample: 1972 2022
Included observations: 51

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.894	0.894	43.216	0.000
		2	0.783	-0.080	77.074	0.000
		3	0.687	0.010	103.66	0.000
		4	0.617	0.070	125.53	0.000
		5	0.572	0.079	144.73	0.000
		6	0.538	0.034	162.10	0.000
		7	0.507	0.016	177.89	0.000
		8	0.468	-0.032	191.67	0.000
		9	0.409	-0.102	202.41	0.000
		10	0.350	-0.012	210.50	0.000
		11	0.301	-0.000	216.63	0.000
		12	0.285	0.114	222.28	0.000
		13	0.284	0.039	228.02	0.000
		14	0.282	0.005	233.84	0.000
		15	0.208	-0.347	237.09	0.000

A visual examination of the correlogram above confirms that the Somalia GDP data is non-stationary. This kind of non-stationary time series, which contains a seasonal trend, can often be carried out by different methods. Before embarking on further analysis using the Box-Jenkins methodology, the data has to be transformed to achieve stationarity.

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Figure 4: Time-series plot for the Somalia GDP data (1st difference)

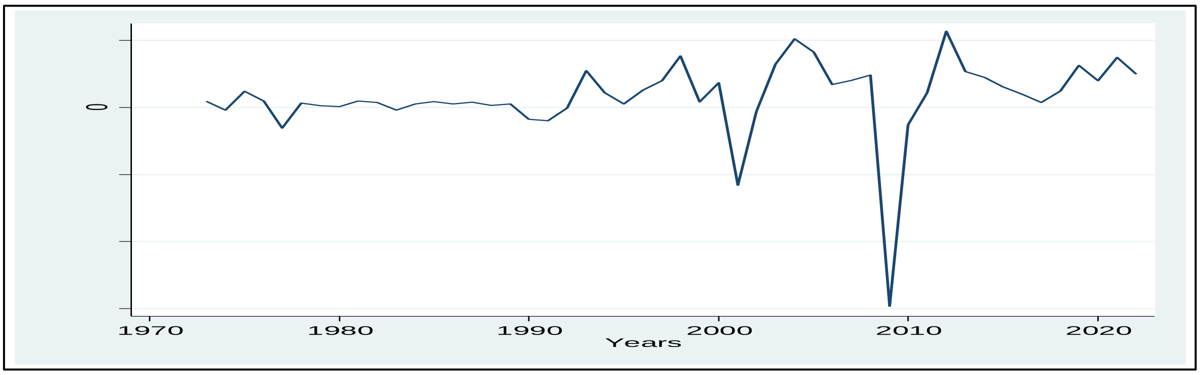
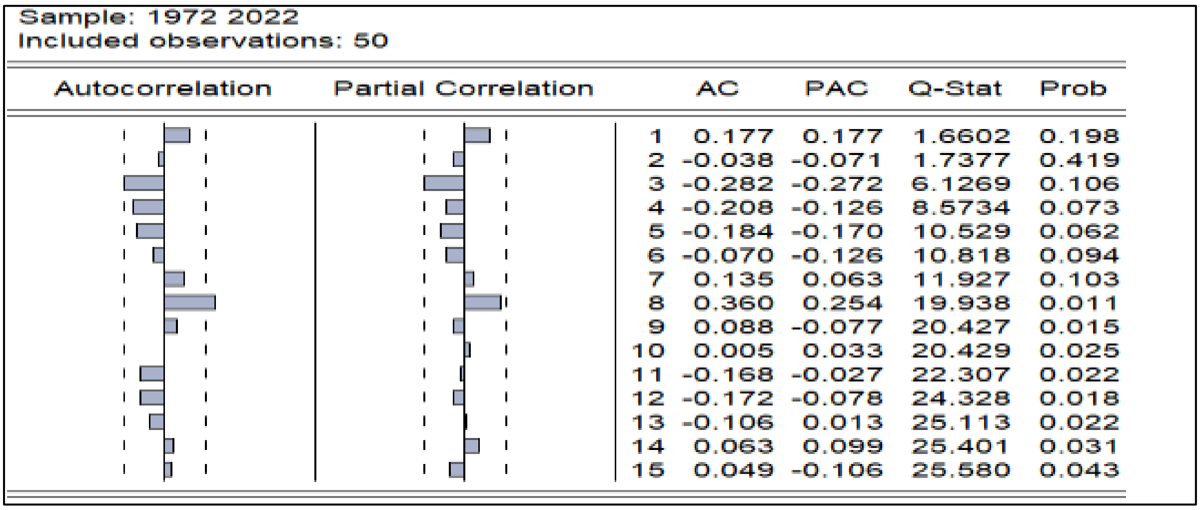


Table 2: Results of ADF Unit Root Test (1st difference) for Somalia GDP data

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Z(t)	-5.705	-3.587	-2.933	-2.601	0.0000

The MacKinnon approximate p-value for Z(t) is 0.0000, which is less than the conventional significance level of 0.05. This further supports the rejection of the null hypothesis and suggests that the differenced Somalia GDP data is statistically significant and stationary. Indicating that it does not possess a unit root and can be suitable for time series analysis using stationary models such as ARIMA.

Figure 5: ACF and PACF plots for first-differentiated Somalia GDP data



Sample: 1972 2022
Included observations: 50

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.177	0.177	1.6602	0.198
		2	-0.038	-0.071	1.7377	0.419
		3	-0.282	-0.272	6.1269	0.106
		4	-0.208	-0.126	8.5734	0.073
		5	-0.184	-0.170	10.529	0.062
		6	-0.070	-0.126	10.818	0.094
		7	0.135	0.063	11.927	0.103
		8	0.360	0.254	19.938	0.011
		9	0.088	-0.077	20.427	0.015
		10	0.005	0.033	20.429	0.025
		11	-0.168	-0.027	22.307	0.022
		12	-0.172	-0.078	24.328	0.018
		13	-0.106	0.013	25.113	0.022
		14	0.063	0.099	25.401	0.031
		15	0.049	-0.106	25.580	0.043

After differencing the data, it is observed in *Figure 5* that the data becomes stationary without any noticeable trend. Therefore, the parameter d in the ARIMA model is determined to be 1. To identify the appropriate values for the remaining two parameters, p and q, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the differenced series are examined and compared with other plots. Based on the analysis, the optimal values are determined to be p = 3 and q = 8. In other words, the suitable model is ARIMA (3, 1, 8).

Estimation and Diagnosis of the ARIMA (3, 1, 8) Model

The estimation results of the ARIMA (3, 1, 8) model are presented in *Table 3*. It is worth noting that the coefficient estimates of the autoregressive component AR (3) are not statistically significant, whereas the coefficient estimate of the moving-average component MA (8) is highly significant at a 1% level of significance. Overall, the model itself is statistically significant at a 1% level of significance.

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Table 3: Parameter estimates of ARIMA (3, 1, 8) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.66E+08	1.41E+08	1.176283	0.2455
AR (3)	-0.191032	0.175825	-1.086492	0.2829
MA (8)	0.467858	0.105438	4.437280	0.0001
SIGMASQ	2.56E+17	3.13E+16	8.200820	0.0000
R-squared	0.230770	Mean dependent var		1.54E+08
Adjusted R-squared	0.180603	S.D. dependent var		5.83E+08
S.E. of regression	5.28E+08	Akaike info criterion		43.12496
Sum squared resid	1.28E+19	Schwarz criterion		43.27792
Log-likelihood	-1074.124	Hannan-Quinn criteria.		43.18321
F-statistic	4.600021	Durbin-Watson stat		1.738849
Prob(F-statistic)	0.006741			

Table 4 presents an evaluation of different ARIMA models based on various goodness-of-fit measures, including the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan Quinn Criterion (HQC). These criteria are commonly used to assess the quality of statistical models, particularly in terms of their ability to balance goodness of fit and model complexity.

Table 4: Evaluation of various ARIMA models

Model	Goodness-of-fit Measure		
	Akaike Info Criterion	Schwar Criterion	Hannan Quinn Criter
ARIMA (3, 1, 3)	43.22817	43.38113	43.28642
ARIMA (3, 1, 8)	43.12496	43.27792	43.18321
ARIMA (8, 1, 8)	43.15183	43.30479	43.21008
ARIMA (1, 1, 8)	43.14392	43.29689	43.20217
ARIMA (1, 1, 3)	43.22468	43.37764	43.28293
ARIMA (8, 1, 3)	43.14494	43.29790	43.20319

Upon examining the table, it is evident that the ARIMA (3, 1, 8) model has the lowest values across all three goodness-of-fit measures. This suggests that the ARIMA (3, 1, 8) model may be the most suitable choice for modelling the data.

According to *Figure 6*, the correlogram of the residuals for the ARIMA (3,1,8) model was examined. The findings suggested that the model could be utilised for estimation purposes since the residuals stayed within the confidence interval. Both the autocorrelation graph and the partial correlation graph did not display any values exceeding the confidence interval. Additionally, all the p-values were greater than 0.05. Consequently, it was concluded that the errors exhibited characteristics of white noise.

Based on the diagram, it can be inferred that the selected ARIMA (3, 1, 8) model is stable. This conclusion is drawn from observing that the inverse roots of the characteristic polynomials associated with the model lie within the unit circle. (see *Figure 7*).

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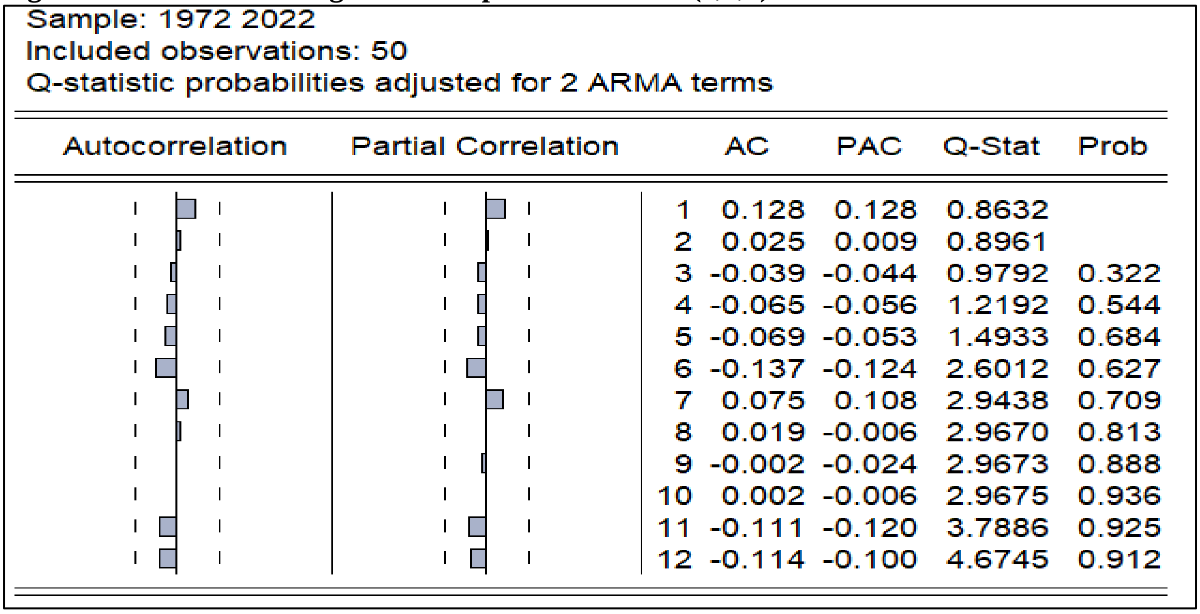
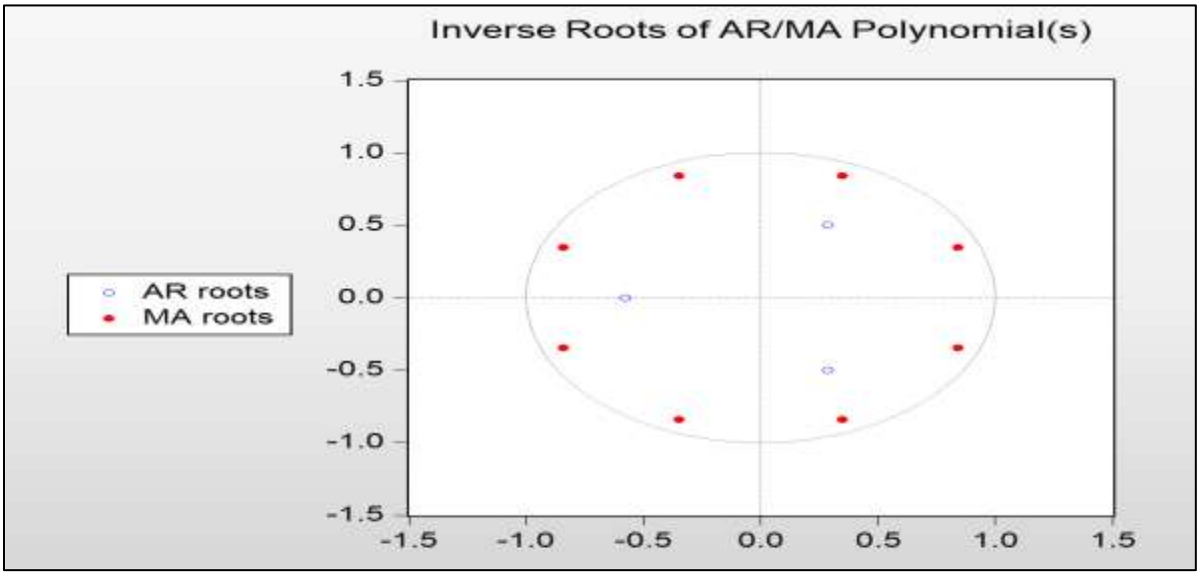
Figure 6: Residual correlogram of the predicted model (3,1,8)


Sample: 1972 2022
Included observations: 50
Q-statistic probabilities adjusted for 2 ARMA terms

	AC	PAC	Q-Stat	Prob
1	0.128	0.128	0.8632	
2	0.025	0.009	0.8961	
3	-0.039	-0.044	0.9792	0.322
4	-0.065	-0.056	1.2192	0.544
5	-0.069	-0.053	1.4933	0.684
6	-0.137	-0.124	2.6012	0.627
7	0.075	0.108	2.9438	0.709
8	0.019	-0.006	2.9670	0.813
9	-0.002	-0.024	2.9673	0.888
10	0.002	-0.006	2.9675	0.936
11	-0.111	-0.120	3.7886	0.925
12	-0.114	-0.100	4.6745	0.912

Figure 7: Inverse Roots of ARMA Polynomials)



Model Forecasting

Since ARIMA (3, 1, 8) model is fit to the GDP data, therefore we can use it to forecast GDP values for the next five years out-of-sample (from 2023 to 2027). The forecasted values of GDP are given in *Table 5* below.

Table 5: Forecasted values of Somalia's GDP

Year	Forecasted GDP	95% Confidence Interval	
		Lower	Upper
2023	8051963507.32035	7238157291.986424	9401524835.204689
2024	8091415524.791954	6804878654.396931	9913627532.9723
2025	8768901968.936158	6938540151.138282	11032312902.56944
2026	9037115105.737185	6937808391.094299	11569901450.33652
2027	9480486951.403464	7072037588.688206	12322858082.21597

The table provides forecasted values of Somalia's GDP for the years 2023 to 2027. The GDP figures are presented in billions of US dollars. Based on the table, Somalia's GDP is projected to

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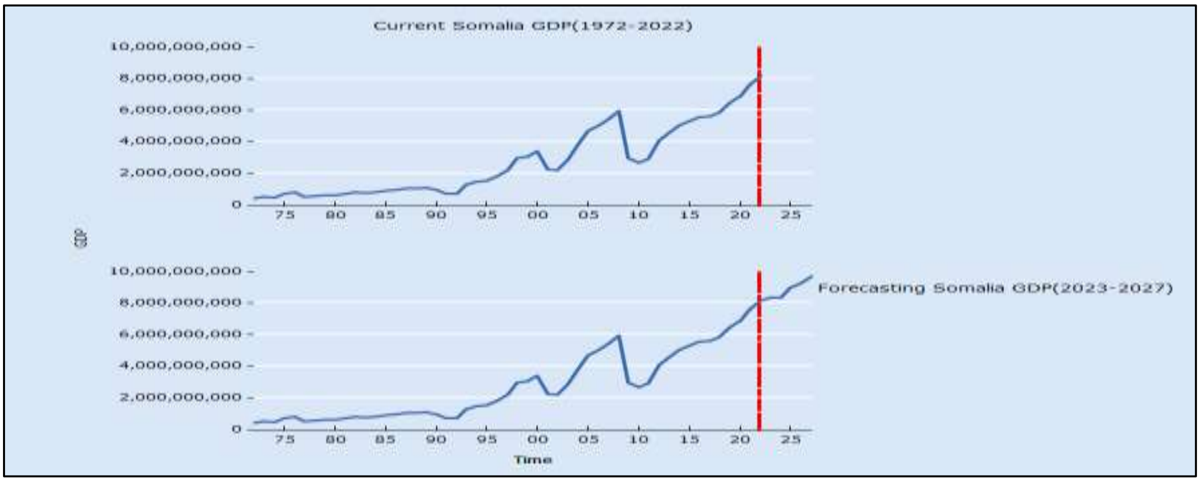
experience steady growth over the forecast period. In 2023, the projected GDP is approximately $8.05 billion, and it gradually increases to $9.48 billion by 2027. The forecasted values indicate a positive trend in Somalia's economic development.

Keep in mind that this result is only a predicted value, but the national economy is a complex and dynamic system. Therefore, we should pay attention to the risk of adjustment in the economic operation and maintain the stability and continuity of the microeconomic regulation and control to prevent the economy from severe fluctuations and adjust the corresponding target value according to the actual situation.

Figure 8: Time series plot for forecasted GDP values



CONCLUSION

This study aimed to employ the Box-Jenkins technique to estimate and forecast Somalia's GDP. Annual data spanning from 1972 to 2022 were utilised for the analysis. By following the four steps of the Box-Jenkins method, an appropriate ARIMA model was identified to capture the underlying patterns in Somalia's GDP dynamics. Subsequently, this selected ARIMA (3, 1, 8) model was applied to generate GDP predictions for the subsequent five-year period, specifically from 2023 to 2027.

Based on the selected ARIMA (3, 1, 8) model, the researcher generated forecasts for the GDP of Somalia for the period from 2023 to 2027. These forecasts provide an estimation of the expected future values of Somalia's GDP, taking into account the historical patterns and trends observed in the data. According to the forecasted values obtained from the model, it is expected that the GDP of Somalia will continue to grow during the specified forecast period. It is important to note that the accuracy and reliability of these forecasts depend on the assumptions and limitations of the ARIMA model and the underlying data. The researchers have made efforts to ensure the model's validity and robustness, but forecasting inherently carries some degree of uncertainty.

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