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MODELING THE GROSS DOMESTIC PRODUCT OF TANZANIA FROM 1960 TO 2023: THE BOX- JENKINS APPROACH

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Abstract

Gross Domestic Product (GDP) is a crucial indicator of a nation's economic performance, reflecting overall economic activity and guiding policy formulation. Accurate GDP forecasting is essential for economic planning, especially in countries like Tanzania, where external shocks such as the COVID-19 pandemic had significantly influenced economic trends. Despite the importance of GDP forecasting, limited studies have analyzed the effectiveness of time series models in predicting Tanzania's GDP before and after major economic shocks. This study employed the Autoregressive Integrated Moving Average (ARIMA) model to forecast Tanzania's GDP at current prices, comparing pre- and post-COVID-19 trends. The research utilizes historical GDP data from 1960 to 2023, obtained from the World Bank. The Box-Jenkins methodology is applied to identify and validate the best-fitting ARIMA model based on statistical criteria such as AIC, BIC, and RMSE. The findings indicate that the ARIMA (0,2,1) model effectively captured Tanzania's GDP trends, offering reliable short-term forecasts. However, external factors such as inflation, global economic fluctuations, and structural inefficiencies continue to pose challenges to long-term economic stability. The study highlights the significance of integrating time series forecasting into economic decision-making, enabling policymakers to anticipate economic shifts and implement evidence-based strategies.

Keywords: Hybrid Models, ARIMA, Economic Shocks, Forecasting

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1. INTRODUCTION

Gross Domestic Product (GDP) serves as a fundamental measure of a country's economic performance, representing the total market value of all final goods and services produced within a nation over a specific period. GDP is calculated based on the value added at each stage of production, from raw materials to final products, typically assessed on an annual basis (Kira, 2023). A robust GDP growth rate is often associated with economic stability, improved living standards, and sustainable development. However, global and domestic economic shocks significantly influence GDP trends, necessitating accurate forecasting models to guide policy and decision-making (Mankiw, 2020).

During 2019, the global economy has faced multiple disruptions, with the COVID-19 pandemic being one of the most significant in modern history. The pandemic led to widespread lockdowns, trade restrictions, and labor market disruptions, causing a sharp contraction in GDP worldwide. Empirical studies have shown that global GDP contracted by approximately 3.4% in 2020, marking one of the steepest declines in recent decades (Mckibbin & Fernando, 2020). Despite gradual recovery through 2021 and 2022, economic projections remain cautious due to ongoing uncertainties, including geopolitical tensions and inflationary pressures (Mulenga, 2024).

According to the International Monetary Fund (IMF), global GDP growth contracted sharply in 2020 due to widespread lockdowns and disruptions to trade, labor markets, and production chains (IMF, 2023). However, in 2021 and 2022, global economic recovery showed signs of resilience, aided by vaccination rollouts and government stimulus packages. Despite this, projections for future global growth remain modest, with growth expected to be 3.3% in 2025 and steady through 2026 (World Bank, 2023). The recovery process has been uneven, with some regions, particularly advanced economies, showing faster recovery, while developing and emerging markets continue to struggle with high levels of debt and inflation (Bailey et al., 2021).

The African economy, particularly in Sub-Saharan Africa, experienced severe economic setbacks due to the pandemic. Several studies have highlighted that GDP growth in Africa plummeted by 2.1% in 2020, marking the worst economic performance in decades (Adegbite, 2023). According to the United Nations Economic commission for Africa (UNECA),the pandemic caused significant disruptions in trade, tourism, and commodity prices, leading to widespread fiscal stress and a sharp contraction in growth across the continent (UNECA,2021).The

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International Monetary Fund (IMF) and the World Bank both reported that recovery prospects for African economies remain uneven, largely dependent on global economic conditions, access to vaccines, and structural reforms (IMF,2021; World Bank,2021) The pandemic exacerbated existing structural challenges such as poverty, inequality, and weak healthcare systems. While economic recovery efforts led to a modest rebound in 2021 and 2022, scholars argue that the region continues to struggle with external debt, inflation, and global supply chain disruptions (Mbaye & Gueye, 2023).

According to the African Development Bank (AfDB), the pandemic caused a severe economic slowdown, with GDP growth in Africa plummeting by 2.1% in 2020, the worst performance in decades (AfDB, 2021). However, as countries began to adapt, economic activity started recovering in 2021, with the AfDB projecting a rebound to 3.4% growth in 2022. Despite this recovery, many African nations continue to face structural challenges that hinder sustainable growth, including limited access to vaccines, poor infrastructure, and dependency on commodity exports (Agwanda et al., 2021). The recovery remains fragile, especially as inflationary pressures and global economic uncertainties persist.

The East African region with a combined population of over 400 million people was also severely impacted by the pandemic. The region, which relies heavily on agriculture, trade, and services, witnessed a GDP contraction of approximately 1.2% in 2020, particularly due to disruptions in tourism and trade (Muoki, 2023). However, economic recovery has been evident, with projections indicating a gradual return to pre-pandemic growth levels, supported by increased trade activities and investments in infrastructure (Geda, 2024). Nevertheless, challenges such as inflation, fluctuating commodity prices, and reliance on external markets continue to pose risks to sustainable growth (Amenu et al., 2023).

East Africa’s GDP contracted by 1.2% in 2020, with tourism, transport, and trade severely impacted (World Bank, 2021). However, recovery in the region has been evident, with projections for 4.5% growth in 2022, led by a resurgence in trade, agriculture, and the mining sectors (United Nations Conference on Trade and Development[UNCTAD], 2021). Despite the regional rebound, East African economies remain vulnerable to global shocks, particularly those related to energy prices and global trade disruptions (Kassegn & Endris, 2021).

In the case of Tanzania, GDP trends have shown fluctuations before and after the COVID-19 pandemic. Prior to 2020, the country’s GDP growth averaged around 6.5%, driven primarily by

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agriculture, manufacturing, and the service sector (Rweyemamu et al., 2023). However, the pandemic significantly slowed economic activities, with GDP growth declining to 2.0% in 2020 (Makoni, 2021). Studies suggest that Tanzania's initial response to the pandemic, including delayed containment measures, contributed to the economic slowdown (Mwakyusa & Masome, 2022). Under recent policy reforms and economic recovery strategies, GDP growth rebounded to 4.6% in 2022, with projections indicating a steady growth rate of 5.2% in 2024 (World Bank, 2024). Despite these positive trends, inflation, global economic uncertainties, and structural inefficiencies remain major concerns for long-term economic stability (Khan & Naushad, 2020).

Recently, the world economy has been showing strength and resilience against all odds, whether it be COVID-19 or the energy crisis (Organization for Economic Cooperation Development [OECD], 2024). Growth of the world's economy is pacing steadily, with a reduction in the upward trend of inflation rates. As labor markets loosened somewhat, unemployment rates remained close to their lows in most countries. The overall level of global trade continued to recover (Pharmaxi & Arriola et al., 2023).

2. MATERIALS AND METHODS

2.1 Data type and source

This study utilizes secondary data spanning from 1960 to 2023 (64 observations), obtained from the world databank- World Development Indicator (WDI). The World Databank is a reputable open-source data platform, widely used in research. The data can be retrieved from the following link; https://databank.worldbank.org/source/world-development-indicators.

2.2 The analysis methods

2.2.1 Autoregressive Integrated Moving Average Model

The Autoregressive Integrated Moving Average (ARIMA) model is a fundamental time series forecasting technique introduced by Box and Jenkins (1970). It combines Auto Regressive (AR), Differencing (I), and Moving Average (MA) components to model and predict time-dependent data. The ARIMA model is represented as ARIMA (p, d, q), where:

- p is the number of autoregressive (AR) terms,
- d is the number of times the series needs to be differenced to make it stationary,
- q is the number of moving average (MA) terms.

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2.2.2 Autoregressive model

The autoregressive (AR) component of a time series model is based on the assumption that the current value of the series depends on a linear combination of its previous values and a random error term. This model assumes that the time series is stationary, meaning that the mean and variance remain constant over time (Box & Jenkins, 1976).However, while stationarity is a key assumption; it does not imply that no diagnostic checks are necessary. In practice, before applying an AR model, it is crucial to perform data diagnostics, such as checking for stationarity using tests like the Augmented Dickey-Fuller (ADF) test or the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Dickey & Fuller, 1979; Kwiatkowski et al., 1992). If the series is non-stationary, transformations like differencing may be required to achieve stationarity before fitting an AR model (Box & Jenkins, 1976).

The general form of the AR(p) model is:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t \qquad (1)$$

Where:

- Y_t is the value of the time series at time t,
- c is a constant term,
- ϕ_i are the autoregressive coefficients,
- p is the number of lagged terms,
- ϵ_t is a white noise error term.

2.2.3 Integrated (I) Component (Differencing for Stationarity)

The integrated (I) component is used to remove trends and make a time series stationary. If a series has a trend, it must be differenced to achieve stationarity. Differencing involves subtracting the previous value from the current value:

$$Y_t^* = Y_t - Y_{t-1}$$

If one difference is not enough, further differencing is applied:

$$Y_t^* = (1 - B)^d Y_t$$

Where:

- B is the backward shift operator $(BY_t = Y_{t-1})_t$
- d is the order of differencing,

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- $(1-B)^d$ represents differencing of order d.

Key Assumptions of Differencing are differencing removes trends but preserves essential structure, and over-differencing can introduce unnecessary complexity and noise.

2.2.4 Moving Average (MA) Component

The moving average (MA) component models a time series as a linear function of past forecast errors. It assumes that current observations depend on past white noise terms rather than past values of the series itself. The general form of the MA (q) model is:

$$Y_t = c + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$$

Where:

- θ_j are moving average coefficients, ϵ_t is the white noise error term, and q is the number of lagged error terms.

Key Assumptions of MA Component are errors are uncorrelated and normally distributed, and the series exhibits short-term shock effects rather than long-term dependencies.

2.2.5 ARMA model

The Autoregressive Moving Average (ARMA) model is a fundamental statistical model used in time series analysis to capture both autocorrelation (dependencies on past values) and random shocks (unexpected variations). The ARMA model was introduced by Box and Jenkins (1970) and is denoted as ARMA (p, q), where:

- p is the number of autoregressive (AR) terms,
- q is the number of moving average (MA) terms.

The ARMA (p, q) model is a combination of Autoregressive (AR) Process which models the current value as a function of past values, and Moving Average (MA) Process which models the current value as a function of past error terms (random shocks).

The general form of the ARMA (p, q) model is:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

Where:

- Y_t is the value of the time series at time t,
- c is a constant term,

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

- ϕ_i are the autoregressive (AR) coefficients,
- θ_j are the moving average (MA) coefficients,
- ϵ_t is a white noise error term (random error with mean zero and constant variance).

The AR and MA terms work together to describe the behavior of the time series. The goal is to capture underlying patterns and randomness in the data. The ARMA model is used for stationary time series, meaning that the data has a constant mean and variance over time. If the series is non-stationary, it must first be differenced, which results in an ARIMA model instead.

2.2.6 ARIMA model

Final ARIMA Model Equation that is obtained after combining all three components, the ARIMA $(\mathrm{p}, \mathrm{d}, \mathrm{q})$ model is given by:

$$\left(1 - \sum_{i=1}^{p} \phi_i B^i\right)(1 - B)^d Y_t = c + \left(1 + \sum_{j=1}^{q} \theta_j B^j\right)\epsilon_t$$

Expanding:

$$\left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)(1 - B)^d Y_t = c + \left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right)\epsilon_t$$

Where:

- $(1 - B)^d$ represents the differencing component.
- $\left(1 - \phi_1 B - \cdots - \phi_p B^p\right)$ represents the autoregressive component.
- $\left(1 + \theta_1 B + \cdots + \theta_q B^q\right)$ represents the moving average component.

This equation shows that ARIMA is essentially an ARMA model applied to a differenced series.

2.3 Stationarity test

2.3.1 Augmented Dickey-Fuller (ADF) Test

The ADF test is an extension of the Dickey-Fuller test and checks for a unit root in the data (Dickey & Fuller, 1979). The test equation is:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t$$

Where:

- $\Delta Y_t = Y_t - Y_{t-1}$ (first difference of the series),

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α is a constant (intercept), βt is a trend term, γ is the coefficient of Y_{t-1}, and p is the number of lagged differences.

Decision Rule:

- If $\gamma < 0$ and statistically significant, the series is stationary.
- If p-value < 0.05, reject H_0, meaning the series is stationary.

2.3.2 Phillips-Perron (PP) Test

The Phillips-Perron (PP) test is similar to the ADF test but makes adjustments for heteroskedasticity and autocorrelation.

The test equation is: $Y_t = \rho Y_{t-1} + \epsilon_t$

where the null hypothesis is: $H_0: \rho = 1$ (non-stationary)

If the p-value < 0.05, we reject H_0 and conclude that the series is stationary.

2.3.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS test is different from ADF and PP because its null hypothesis assumes stationarity

The test equation is: $Y_t = rt + X_t + \epsilon_t$

Where r is the deterministic trend and X_t is a stationary process.

Decision Rule:

- If p-value < 0.05, reject H_0 meaning the series is non-stationary.

2.3.4 Differencing method

Differencing is a technique used in time series analysis to remove trends and make a non-stationary series stationary. It transforms a series where values depend on time into one where statistical property (mean, variance, and autocorrelation) remain constant. The differencing method is crucial for ARIMA models, where stationarity is required for accurate forecasting**.** The first-order difference of a time series Y_t is given by:

$$\Delta Y_t = Y_t - Y_{t-1}$$

where:

- Y_t is the current observation.
- Y_{t-1} is the previous observation.
- ΔY_t is the differenced series.

If first-order differencing does not achieve stationarity, we apply second-order differencing:

$$\Delta^2 Y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$$

FORCE: Focus on Research in Contemporary Economics *2025 - Vol:6 No:1*

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In general, for dth order differencing:

$$\Delta^d Y_t = Y_t - Y_{t-d}$$

where d is the number of differences needed to make series stationary.

2.4 Box-Jenkins methodology for ARIMA Modeling

The Box-Jenkins methodology for ARIMA modeling is a systematic approach to time series forecasting that involves four main steps: model identification, parameter estimation, diagnostic checking and forecasting. Box and Jenkins (1970) proposed a systematic way to build an ARIMA model using four key steps:

2.4.1 Model identification

A preliminary Box-Jenkins analysis should begin with plotting the raw data to determine a suitable model. The data must be transformed into a stationary series, with seasonal patterns identified and addressed through seasonal differencing if needed. Additionally, examining the autocorrelation and partial autocorrelation function (ACF and PACF) plots of the dependent time series helps determine whether to include autoregressive (AR) or moving average (MA) components in the model.

2.4.2 Autocorrelation function

The Autocorrelation Function (ACF) measures the linear relationship between current and past values of a time series at different lags. Mathematically, the autocorrelation at lag k is given by:

$$\rho(k) = \frac{\sum_{t=k+1}^{n} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n} (Y_t - \bar{Y})^2}$$

where:

- Y_t is the time series at time t, $\bar{Y}$ is the mean of the series, k is the lag, and n is the total number of observations.

Use of ACF in Identifying MA (q) Models

- In a pure MA (q) model, the ACF cuts off after **q** lags and becomes approximately zero beyond lag q.
- This means that for a MA (1) process, only the first lag has a significant autocorrelation, and the rest are insignificant.

2.4.3 Partial autocorrelation function

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The Partial Autocorrelation Function (PACF) measures the correlation between the current time series value and a past value, removing the effects of the intermediate lags.

PACF at lag k is computed using the Yule-Walker equations, and it is defined as the coefficient in the regression equation:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_k Y_{t-k} + \epsilon_t$$

where:

- ϕ_k is the partial autocorrelation at lag k,
- ϵ_t is the error term.

Use of PACF in Identifying AR(p) Models

- In a pure AR(p) model, the PACF cuts off after **p** lags and becomes approximately zero beyond lag p.
- This means that for an AR(1) process, only the first lag has a significant PACF, and the rest are insignificant.

2.4.4 Parameter Estimation

In the Box-Jenkins methodology, parameter estimation involves determining the optimal values for the parameters of the autoregressive (AR) and moving average (MA) components of the model, as well as the differencing order (d). This is typically done using methods like Maximum Likelihood Estimation (MLE) or Least Squares. After estimating the parameters, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to evaluate the model's goodness-of-fit while penalizing for complexity, helping in model selection. The model with the lowest AIC or BIC is preferred, as these criteria balance model accuracy with parsimony, minimizing over fitting. AIC and BIC are critical in selecting the best ARIMA model by comparing models with different combinations of p, d, and q parameters.

Akaike Information Criterion (AIC)

AIC is a measure that evaluates the relative quality of a statistical model. It considers both the likelihood of the model (how well it fits the data) and the number of parameters in the model (to penalize complexity). The formula for AIC is:

$$\text{AIC} = 2k - 2\ln(L)$$

where:

- k is the number of parameters in the model.
- L is the likelihood of the model (the probability of the data given the model).

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

A lower AIC value indicates a better model, as it suggests a model that fits the data well without excessive complexity. When comparing models, the one with the lowest AIC is preferred.

Bayesian Information Criterion (BIC)

BIC is similar to AIC but applies a stronger penalty for the number of parameters, especially in models with a large sample size. The formula for BIC is:

$$\text{BIC}=\ln(n)\,k-2\ln(L)$$

where:

- n is the number of observations (sample size).
- K is the number of parameters.
- L is the likelihood of the model.

BIC also prefers models with lower values. It imposes a larger penalty for including more parameters compared to AIC, so it tends to select simpler models when the sample size is large.

Diagnostic checking

Diagnostic checking refers to the process of validating a time series model by analyzing its residuals (the difference between observed and predicted values). This step helps assess whether the model accurately captures the underlying data patterns and whether any further improvements or modifications are needed. Diagnostic checking is done after fitting the model, which includes the steps of identification, estimation, and model selection. The main goals of diagnostic checking are to Validate the model assumptions (e.g., residuals should be normally distributed with a mean of zero), Identify any remaining patterns in the residuals, which might indicate that the model has not fully captured all relevant information and to ensure the residuals resemble white noise (random, uncorrelated errors), indicating that no further structure is left to model.

Tools like the Ljung-Box test, Autocorrelation Function (ACF) plots, and histograms of residuals are used in this step. If significant autocorrelation or patterns remain in the residuals, the model might need to be adjusted or re-estimated to better fit the data.

2.5 Forecasting

Selecting an appropriate forecasting model for time series prediction requires the use of suitable forecasting tools. However, the choice of a specific model does not automatically guarantee its effectiveness for prediction. To ensure the selected model is truly suitable for forecasting, it is essential to evaluate its performance using error measurement metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These metrics help

Received: 05.08.2025 *Accepted: 28.08.2025* *Published:29.08.2025*

verify that the chosen model accurately represents the time series data and is reliable for making future predictions.

Mean Square Error (MSE)

Mean Squared Error is a common metric used to evaluate the performance of a predictive model. It measures the average of the squared differences between the predicted values and the actual values. The MSE is defined as:

$MSE = 1/n \sum_{t=1}^{m} \varepsilon_t^2$ Where, ε_t is defined by $\varepsilon_t = Y_i - \hat{Y}_i$

Where, ε_t stands for error term, Y_i stands for observational values, $\hat{Y}_i$ stands for forecasting values, t is the time and m are the total observational data (Phinikarides et al., 2013). MSE gives a high penalty to large errors, as the errors are squared. A smaller MSE indicates better predictive performance of the model, as it means the predictions are closer to the actual values.

Mean Absolute Error (MAE)

Mean Absolute Error is a fundamental metric used to assess the accuracy of a forecasting model. It represents the average of the absolute differences between predicted and actual values, making it one of the simplest and most interpretable error measures. MAE quantifies how much, on average, the model's predictions deviate from the actual observations, without considering the direction of the errors. A lower MAE value indicates a better-performing model with more accurate predictions (Elsaraiti & Merabet, 2021).

Mathematically, MAE is defined as follows (Elsaraiti & Merabet, 2021):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|Y_i - \hat{Y}_i\right|$$

Where:

- n is the total number of observations,
- Y_i represents the actual values,
- $\hat{Y}_i$ represents the predicted values,
- $\left|Y_i - \hat{Y}_i\right|$ is the absolute error for each observation.

Since MAE does not square the errors like Mean Squared Error (MSE), it retains the original scale of the data, making it easy to interpret. However, it treats all errors equally without giving more weight to larger deviations.

Root Mean Square Error

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Root Mean Squared Error (RMSE) is simply the square root of the Mean Squared Error (MSE). It is another common metric used to evaluate the performance of a model, particularly when we want to express the error in the same units as the original data, making it more interpretable (Elsaraiti & Merabet, 2021). The RMSE is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(y_{\text{predicted}} - y_{\text{actual}}\right)^2}{n}}$$

where, $y_{\text{predicted}}$ are the predicted values of the observations, y_{actual} are the actual values of the observations and n gives the total number of observations (Elsaraiti & Merabet, 2021). When the value of measure of error is around zero, then it means that model has the perfect skills for forecasting or in other words we say the models has no errors (Quarrie et al., 1998). It is important to note that when the values of measures of errors are smaller, it indicates that the model is the best for forecasting purposes. In general, a lower RMSE indicates a better fit of the model to the data.

3. RESULTS AND DISCUSSION

3.1. Descriptive analysis

Table 1 shows the descriptive statistics of the GDP following by a discussion underneath.

Table 1: Descriptive statistics of the GDP in USD billion (TZ) at current prices, 1960-2023.

Description	Statistic (Billion USD)
Mean	19475498880
Median	11283713014
Standard deviation	20542033811
Minimum	2651729807
Maximum	79062403821
Skewness	1.494880397
Kurtosis	4.059595746

Source: Created by authors

Table 1 shows the result of the descriptive analysis of GDP of Tanzania at current prices, revealing key statistical insights into its distribution and growth pattern. The mean GDP is $19.48 billion,

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indicating the average economic size over the period, while the median GDP of $11.28 billion suggests that half of the observations fall below this value. The standard deviation of $20.54 billion highlights significant variability in GDP, reflecting substantial economic expansion over time.

The minimum GDP recorded was $2.65 billion, while the maximum reached $79.06 billion, illustrating a strong upward trend in economic performance. The skewness value of 1.49 indicates a right-skewed distribution, meaning GDP values are concentrated on the lower end with higher values in recent years. Furthermore, the kurtosis of 4.06 suggests a leptokurtic distribution, indicating the presence of a few extreme values that have significantly influenced the overall GDP trend. These findings confirm Tanzania's consistent economic growth, albeit with fluctuations over the years.

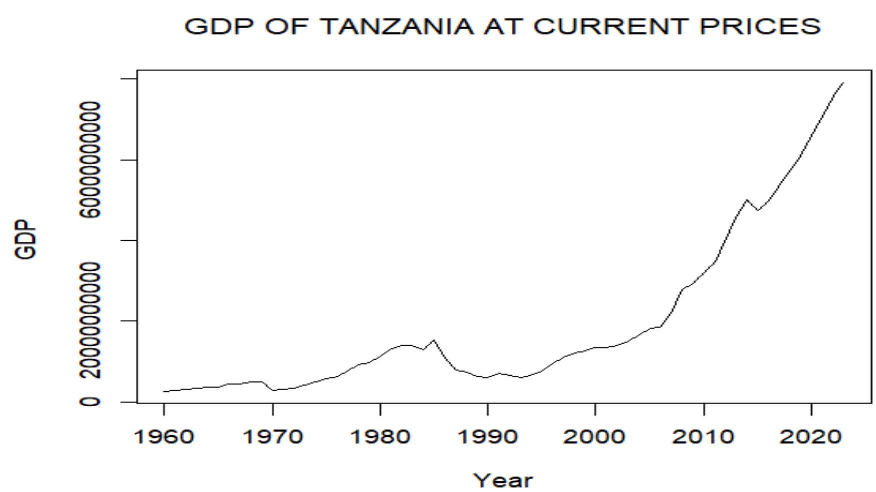

Figure 1: Trend Analysis of GDP (USD billion) at current price of Tanzania

Source: Created by authors

As observed the GDP at current prices trend of Tanzania from 1960 to 2023 shows an overall upward trajectory, indicating economic growth over time. However, the peaks in the GDP values do not repeat at regular intervals or with the same intensity, suggesting irregularities and fluctuations in the growth pattern. This behavior points to non-stationary in the data, where statistical properties like mean and variance change over time due to various economic factors. To address this, transformations using differencing method where first differencing (d=1) was not enough when applied to make the series stationary hence second differencing (d= 2) transformed data into stationary. This is in agreement with (Enders, 2015) that when time series data is not

FORCE: Focus on Research in Contemporary Economics 2025 - Vol:6 No:1
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stationary, performing differencing will make the data stationary, and therefore further analysis can be carried out, as also suggested in Cheti and Ilembo (2021). The Dickey-Fuller test further confirmed the stationarity after transformation, making the data suitable for reliable forecasting and analysis.

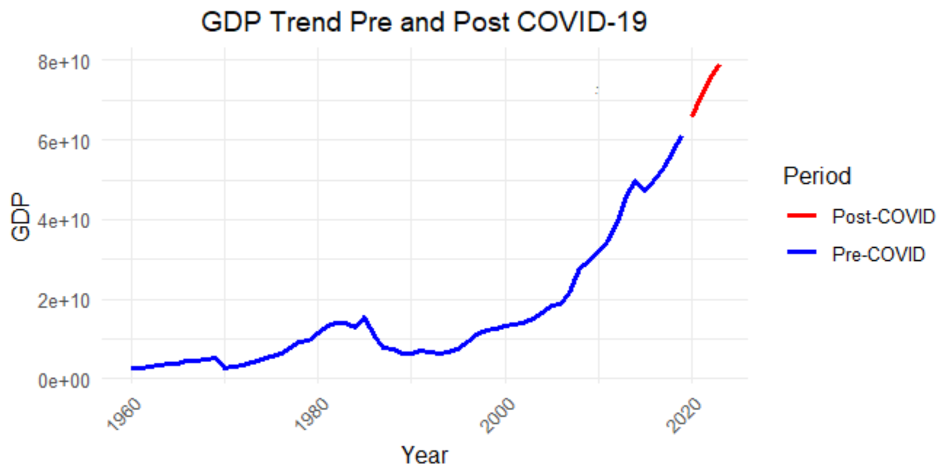

Figure 2: Trend of GDP Pre and Post COVID-19

Source: Created by authors

Figure 2 illustrates Tanzania's GDP at current prices trend from 1960 to the post-COVID-19 period, distinguishing between pre-COVID and post-COVID trends using different colors. The blue line represents GDP growth before the pandemic, showing a general upward trajectory with occasional fluctuations. Notably, GDP growth appears relatively stable but exhibits significant acceleration in the 2000s, reflecting economic expansion.

However, the post-COVID GDP trend, represented by the red segment, suggests continued growth despite potential disruptions caused by the pandemic. (Capello, et. al., 2021). The visualization implies that Tanzania's economy remained resilient, continuing its upward trajectory even after the global economic downturn induced by COVID-19. The consistent rise in GDP post-COVID may indicate strong economic policies, recovery efforts, and structural growth factors supporting Tanzania's economy. However, further analysis would be required to determine the pandemic's specific impacts and whether growth has been slowed or accelerated relative to pre-COVID projections. As also suggested by Chirwa (2023).

FORCE: Focus on Research in Contemporary Economics 2025 - Vol:6 No:1
Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

These observation is consistent with assessment by institutions such as the World Bank and the International Monetary Fund (IMF), both of which have noted Tanzania`s relative economic resilience during the pandemic period, attributing it to a combination of targeted fiscal measure, less severe lockdown restrictions, and the country`s diversified economic base (World Bank, 2022; IMF, 2022).

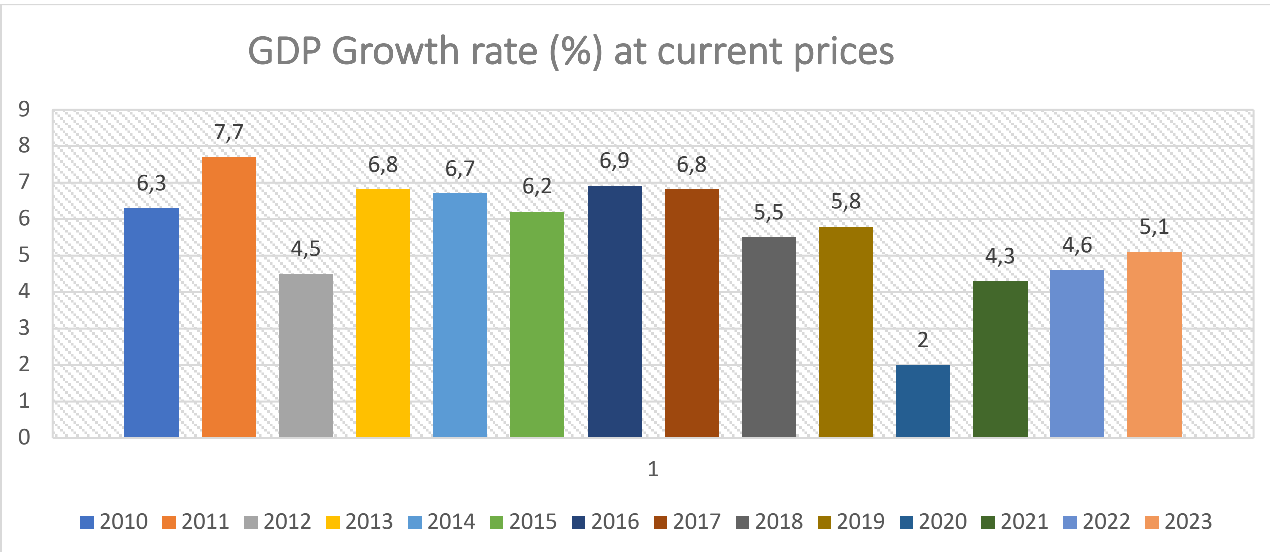

Figure 3: GDP Growth rate at current prices (USD billion) analysis from 2010-2023

Source: Created by authors

Figure 3 shows a clustered-column chart of GDP growth rate of Tanzania at current prices which demonstrated a clear distinction between the pre-COVID-19 (2010–2019) and post-COVID-19 (2020–2023) periods. Before the pandemic, Tanzania exhibited strong and stable economic growth, with rates fluctuating between 6.2% and 7.7%, reaching its peak in 2011 at 7.7%.

However, in 2020, during the COVID-19 crisis, the growth rate sharply declined to 2%, reflecting the economic disruptions caused by lockdowns, reduced trade, and global economic slowdowns. In the post-pandemic period (2021–2023), the economy shows signs of recovery, with GDP growth rising to 4.3% in 2021, 4.6% in 2022, and 5.1% in 2023. Although the growth is improving, it has not yet returned to pre-pandemic levels, indicating a gradual recovery process.

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

3.3 Stationarity tests

A stationarity test is used to determine whether a time series has constant statistical properties, such as mean and variance over time an essential, requirement for accurate ARIMA modeling. Ensuring stationarity helps prevent misleading forecasts and ensures the model`s reliability. Table 2 presents the summary of the stationarity test results

Table 2: Stationarity tests to check stationarity of time series data

Test	Statistic	P-value
ADF Test	0.9363159665	0.990
Phillips-Perron Test	4.1177851151	NA

Source: Created by authors

Table 2 shows the results of the stationarity tests. The Augmented Dickey-Fuller (ADF) test returned statistics of 0.9363 ($p = 0.990$), which is greater than the 0.05 significance level, meaning we fail to reject the null hypothesis that the series has a unit root. This suggests that GDP follows a trend and is not stationary. Similarly, the Phillips-Perron (PP) test produced a test statistic of 4.1178, which, when compared to typical critical values, further confirms that the series is non-stationary. The absence of a p-value for the PP test means we rely on its test statistic, which aligns with the ADF results.

Since GDP at current prices exhibits a trend over time, any shocks to the economy are likely to have long-term effects rather than temporary fluctuations. This also implies that direct time series modeling using ARIMA or other forecasting techniques requires transformation. To make the series stationary, first differencing should be applied followed by rechecking stationarity using the same tests. Once the series is made stationary, appropriate time series model which is ARIMA, is fitted for forecasting purposes.

Table 3: Stationarity tests to check stationarity for the differenced time series data

Test	Statistic	P-value
ADF Test	-6.12408940397	0.010
Phillips-Perron Test	-66.39398834784	NA

Source: Created by authors

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After confirming that the GDP series at current prices was non-stationary, first differencing was applied to remove the trend. However, the stationarity tests still indicated the presence of a unit root, suggesting that first differencing was insufficient. Consequently, second differencing was applied, which successfully transformed the series into a stationary form.

Table 3 shows the results of the Augmented Dickey-Fuller (ADF) test which showed a statistic of -6.1241 with a p-value of 0.010, allowed the rejection of the null hypothesis of a unit root, confirming stationarity.

Additionally, the Phillips-Perron (PP) test resulted in a highly negative statistic of -66.394, reinforcing the conclusion that the GDP series became stationary after the second differencing. These results confirmed that the original GDP series required second differencing to achieve stationarity, thereby making it suitable for time series modeling and forecasting

3.4 ARIMA Modeling Using the Box-Jenkins Methodology

After successfully transforming the GDP time series into a stationary form through second differencing, the next step involves applying the Box-Jenkins methodology to develop an ARIMA model using RStudio. The Box-Jenkins approach follows a structured process of model identification, parameter estimation, and diagnostic checking to ensure the best-fitting model is selected. With stationarity achieved, the next step is examining the ACF and PACF plots to determine appropriate values for the autoregressive (p) and moving average (q) components. The **auto.arima** function in R is used to identify an optimal ARIMA model by selecting the best model based on information criteria, such as the AIC and BIC. After the model is estimated, residual diagnostics are conducted to evaluate the adequacy of the model. This step ensures that the residuals resemble white noise. A well-specified ARIMA model is then used to forecast Tanzania's GDP trends, providing valuable insights for economic planning and policy formulation

Model identification and selection

The model identification phase involved examining the stationarity of the GDP time series Andrei & Bugudui (2011). Once stationarity was achieved, the selection of AR and MA terms is optimized and automated using the auto. arima () function in RStudio, which systematically evaluates multiple ARIMA specifications and selects the best-fitting model based on statistical criteria such as AIC and BIC. This function helped to eliminate the need for manual trial-and-error selection by

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

efficiently scanning through a range of model configurations and determining the most appropriate structure for the data.

The ARIMA(0,2,1) model was selected as the best-fitting model for forecasting GDP, The series was differenced twice (d = 2) to remove long-term trends and achieve stationarity. The presence of a moving average component of order 1 (MA (1) = -0.7174) suggests that the model accounts for short-term shocks in GDP fluctuations, meaning that the current GDP value is influenced by past forecast errors. The absence of an autoregressive component (p = 0) indicates that past GDP values beyond differencing do not significantly contribute to the predictions.

The selection of the ARIMA (0,2,1) model was based on the AIC and BIC, both of which measure model performance while penalizing complexity. The selected model had the lowest AIC and BIC values compared to alternative specifications, confirming its suitability for GDP forecasting.

Model Estimation

The model parameters were estimated using the auto. arima () function in R software, which automatically selects the best ARIMA model by evaluating various combinations of autoregressive (AR), differencing (I), and moving average (MA) terms. This function uses maximum likelihood estimation (MLE) to estimate the coefficients, including the MA (1) coefficient of -0.717 in the selected ARIMA (0,2,1) model.

Diagnostic checking

i. *Ljung-Box test*

The Ljung-Box test was performed to check for autocorrelation in the residuals to assess adequacy of the ARIMA (0,2,1) model for GDP forecasting. The Ljung-Box test evaluates whether the residuals of the fitted model are independent (white noise) or if they still exhibit significant patterns, which would indicate model inadequacy.

Table 4: Ljung Box test for the residual

x^2	Degree of freedom	p-value
7.3406	8	0.5004

Source(s): Created by author

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

Table 4 shows that p-value (0.5004) is greater than compared to the standard significance level ($\alpha = 0.05$), we fail to reject the null hypothesis (H_0). This suggests that there is no significant autocorrelation in the residuals, meaning the residuals are uncorrelated and purely random distributed. Consequently, the ARIMA (0,2,1) model is considered adequate and well-specified, as it effectively captures the time series structure without leaving systematic patterns in the residuals.

ii. ACF plot for residual

ACF plot of the residuals is a crucial diagnostic tool used to assess whether the ARIMA (0,2,1) model has adequately captured the underlying structure of the GDP time series.

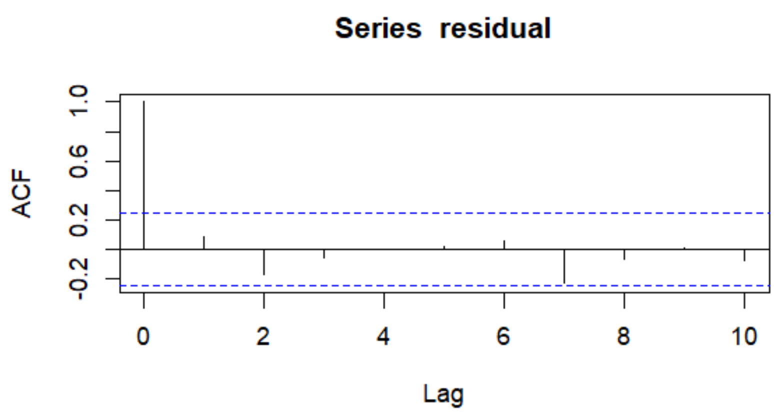

Figure 4: ACF plot for residual

Source: Created by authors

In figure 4, the autocorrelations at different lags are displayed, with blue dashed lines representing the confidence bounds (typically at the 95% confidence level). Most autocorrelation values fall within these bounds, which it suggests that the residuals exhibit no significant autocorrelation, indicating that the model has effectively removed systematic patterns from the data.

Since the ACF plot does not show any significant autocorrelation, the residuals appear to be random and uncorrelated, confirming that the ARIMA (0,2,1) model is well-specified. This supports the results from the Ljung-Box test, further validating that the model is appropriate for GDP forecasting and does not require additional modifications.

Received: 05.08.2025 Accepted: 28.08.2025 Published:29.08.2025

Validating the model

Model validation is conducted to evaluate how accurately the model estimates the observed values. The predicted forecasts for the validation set are compared visually by plotting them alongside the actual data.

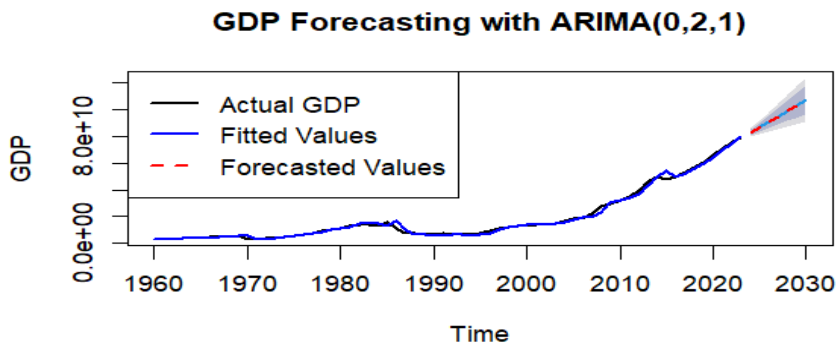

Figure 5: GDP forecasting

Source: Created by authors

Figure 5 shows the plotted GDP forecasting results using the ARIMA (0,2,1) model provide a clear visualization of the model's performance. The black line, representing actual GDP values, allows for direct comparison with the blue line (fitted values) and the red dashed line (forecasted values). The close alignment between the blue fitted values and the black actual values indicates that the model has effectively captured historical trends, demonstrating a strong fit.

Furthermore, the red forecasted values extend logically from the fitted trend, suggesting that the model provides reliable future GDP predictions. The absence of large deviations between the fitted and actual values further confirms the model's accuracy and effectiveness in forecasting GDP.

Accuracy Measurement

The accuracy of the ARIMA (0,2,1) model for GDP forecasting is evaluated using multiple error metrics from the training set. The Mean Percentage Error (MPE = 1.018%) and Mean Absolute Percentage Error (MAPE = 8.83%) provide a relative measure of forecast accuracy, showing that the model's predictions deviate by approximately 8.83% on average from actual GDP values. Since MAPE is below 10%, the model demonstrates reasonable predictive performance.

The Mean Absolute Scaled Error (MASE = 0.5967), being less than 1, suggests that the ARIMA model performs better than a naive forecasting approach. Lastly, the Autocorrelation of Residuals

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at Lag 1 ($ACF_1 = 0.0863$) is close to zero, confirming that the residuals exhibit minimal correlation, meaning the model has adequately captured the time series patterns without significant remaining dependencies. These accuracy metrics collectively indicate that the ARIMA (0,2,1) model provides a reasonably accurate and reliable forecast for GDP trends.

3.5 Forecasting

Based on the ARIMA (0,2,1) model, GDP at current prices from 2024 to 2030 is provided in Table 5, and Figure 6 shows the trend of forecasted GDP at current prices in USD billion of Tanzania.

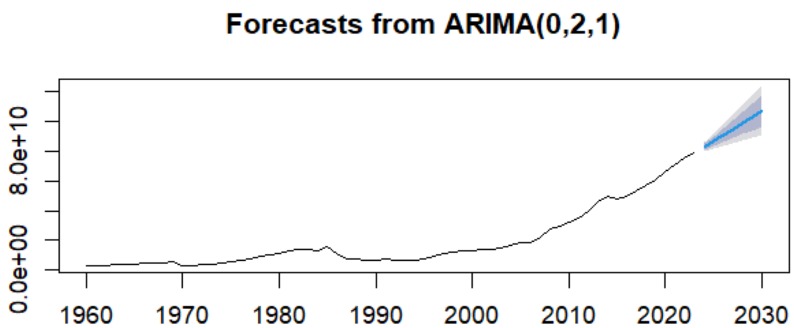

Figure 6: Model validation of GDP at current prices of Tanzania using ARIMA (0,2,1)
Source: Created by authors

Table 5: Forecasted values for the GDP at current prices of Tanzania in USD billion at 95% confidence interval

Time	Forecast	Lower (95% CI)	Upper (95% CI)
2024	83,080,028,892	79,847,506,796	86,312,550,988
2025	87,097,653,964	81,840,352,574	92,354,955,353
2026	91,115,279,035	83,818,755,901	98,411,802,169
2027	95,132,904,106	85,703,244,069	104,562,564,143
2028	99,150,529,177	87,473,794,743	110,827,263,612
2029	103,168,154,249	89,125,670,165	117,210,638,333
2030	107,185,779,320	90,659,334,499	123,712,224,142

Source: Created by authors

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The forecast plot from the ARIMA (0,2,1) model provides projections for GDP from 2024 to 2030 based on historical trends. The black line represents the actual GDP data from 1960 to 2023, showing a general upward trend with some fluctuations. The forecasted values shown in blue extend beyond the observed data, indicating continued GDP growth.

The shaded areas around the forecast represent the 95% confidence intervals, with the darker blue indicating higher confidence and the lighter gray regions showing a wider uncertainty range. As time progresses, the confidence intervals widen, reflecting increasing uncertainty in long-term forecasts.

From Table 5 of the forecasted values, GDP is expected to increase from 83.08 USD billion in 2024 to approximately 107.19 USD billion in 2030. The lower and upper bounds provide a range within which GDP is likely to fall, with a growing gap as time advances due to accumulated uncertainty.

Overall, the ARIMA (0,2,1) model suggests that Tanzania's GDP will continue its upward trajectory, aligning with historical growth patterns. However, the widening prediction intervals indicate that future GDP values could vary depending on economic policies, external shocks, or global economic conditions.

4. CONCLUSION

The findings revealed that while Tanzania's economy has experienced consistent long-term growth, it remains vulnerable to external shocks, as seen in the sharp decline in GDP growth to 2% in 2020 due to the pandemic. However, the rapid recovery to 4.6% growth in 2022 highlighted the country's economic resilience, driven by policy interventions, adaptive industries, and the gradual reopening of global markets. The model forecasts steady growth, projecting a 5.2% increase in GDP by 2024, signaling a positive outlook for the nation's economic trajectory.

This study analyzed Tanzania's GDP trends before and after the COVID-19 pandemic, using the ARIMA model to assess economic performance and forecast future growth. The findings indicate that Tanzania's GDP exhibited steady growth before 2020, averaging around 6.5%, but experienced a sharp decline to 2.0% in 2020 due to the economic disruptions caused by the pandemic. However, the economy demonstrated resilience, with GDP rebounding to 4.6% in 2022 and projected to stabilize at 5.2% in 2024.

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These findings emphasize that, despite external shocks, Tanzania's economic structure and policy interventions have enabled recovery and sustained progress. However, the study acknowledges limitations, as ARIMA models, while powerful, may struggle to capture sudden economic disruptions or structural breaks caused by unforeseen crises.

Despite the robustness of the ARIMA model, the study acknowledged certain limitations. The model relies solely on past values and may struggle to account for sudden, unexpected shocks or structural changes in the economy. For instance, factors like inflation, exchange rates, and global commodity prices all of which significantly influence GDP were not included as independent variables. Incorporating these variables in future research could improve forecast accuracy and offer a more nuanced understanding of the drivers of economic growth.

Future research could enhance forecasts by integrating additional variables, such as inflation rates, global commodity prices, and regional trade dynamics, to build a more comprehensive economic outlook. Ultimately, this research underscores the value of data-driven forecasting for guiding policy decisions and reinforcing Tanzania's long-term growth trajectory.

Overall, the study concludes that statistical modeling, when combined with sound economic analysis, can be a powerful tool for informing policy decisions. The insights gained from this research provide policymakers with valuable information to guide resource allocation, design targeted interventions, and build economic resilience. However, sustaining growth will require continuous monitoring of global and domestic conditions, proactive policy adjustments, and strategic investments in sectors with high growth potential. By embracing data-driven decision-making and addressing structural vulnerabilities, Tanzania can not only achieve sustained GDP growth but also position itself as a rising economic powerhouse in East Africa and beyond.

5. POLICY IMPLICATIONS

The findings of this study offer valuable insights for policymakers, development planners, and government officials in Tanzania, emphasizing the need for proactive, evidence-based strategies to sustain GDP growth and build economic resilience. First, the government should prioritize economic diversification by strengthening sectors like manufacturing, agribusiness, and digital services to reduce reliance on tourism and primary commodities, which are highly vulnerable to global market fluctuations.

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Investing in infrastructure development, education, and technological innovation can unlock new growth drivers and increase the country's competitiveness. Additionally, the study highlights the critical role of adaptive fiscal and monetary policies during crises policymakers should build contingency frameworks that allow for rapid adjustments to interest rates, targeted subsidies, and strategic public spending to cushion against future shocks. Strengthening data collection and statistical capacity will also enhance policy precision, enabling decision-makers to continuously monitor economic indicators and adjust strategies in real time.

Finally, fostering regional and global integration through trade agreements, foreign direct investment incentives, and participation in regional value chains can shield the economy against external disruptions while expanding market access for Tanzanian goods and services. By leveraging these policy insights and maintaining a forward-looking approach, Tanzania can not only safeguard its economic progress but also position itself as a resilient and dynamic player in the global economy.

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DISCLOSURE OF CONFLICT

The author(s) declare that they have no conflicts of interest.