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Forecasting Kenya's public debt using time series analysis

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ABSTRACT

Accurately forecasting public debt is essential for developing countries like Kenya to maintain fiscal sustainability and economic stability. This study aimed to identify the best time series forecasting model for predicting Kenya's future public debt to help policymakers create effective fiscal reforms. The Autoregressive Integrated Moving Average (ARIMA) and Holt-Winters exponential smoothing models were tested due to their ability to handle complex patterns and seasonality in time series data. Public debt data from Kenya from 2001 to 2021 were analyzed, and both models were applied to the processed data. The ARIMA (0,2,1) model, which uses second-order differencing and a moving average component, was found to be the best model based on information criteria. The Holt-Winters additive method also showed good performance, adapting well to recent data and seasonal trends with optimized smoothing parameters. Both models produced forecasts that closely matched the actual debt figures for 2022 and 2023, with an error margin of only 0.73. Measures of accuracy, such as Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE), confirmed the reliability of the models, with ARIMA performing slightly better than Holt-Winters. While previous studies have looked at debt forecasting for Kenya, this research offers a thorough evaluation and comparison of two strong time series models. Unlike existing literature, this study provides a rigorous out-of-sample forecasting assessment, identifying the best approach for reliably predicting Kenya's debt. However, the study is limited by its focus on univariate time series models, which could be improved by including relevant external economic variables. The findings show that the ARIMA and Holt-Winters models are accurate tools for forecasting Kenya's public debt, helping policymakers to develop sustainable debt management strategies and fiscal reforms based on reliable future projections.

1. Introduction

Over the decades, there has been a rapid increase in the public debts in Kenya, both domestic and external debt (Makau et al., 2018). The huge debt burden has resulted in over-taxation of the basic commodities to repay the loan. This has led to a rise in the prices of basic commodities and consequently lowering the standards of living among Kenyans (Kithure, 2021). Barro (1979) argued that public debt arises when the total income generated through the taxation system and other available sources is sufficiently lower than government spending. He says that a constant source of income cannot compete with the ever-increasing government expenditure, thus resulting in public debt because the government budget, or expenditure, for that matter, is always a function of the total income, which is mostly constituted by taxes.

Several studies have been done to predict public debt trends globally. In Kenya, only a few studies have been done to project the future trend of the country's debt. For instance, studies done by Mwaniki (2016), Nyaga and Ng'ang'a (2015), and Motonu et al. (2016) researched Kenya's public debt. The available information is not enough for economists and policy formulators to anticipate how to control public debt, which is a major economic problem. Therefore, this study aimed to forecast future debt in Kenya, thereby availing sufficient information that will help policy formulators develop policies that will help reduce the rate of borrowing and advise on ways to finance the government. This research study will use a time

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series modeling technique to forecast Kenya's future public debt. The ARIMA and Holt exponential smoothing models will be applied to fit the public debt dataset, and a comparison between the two models will be made using the Root Mean Square Error to identify the best-fitting model.

The issue of escalating public debt has been a major concern in Kenya, with several recent studies investigating its implications on the country's economic growth and stability. Mutunga (2020) utilized a Vector Autoregression (VAR) model to examine the effect of public debt on Kenya's future economic growth, finding that public debt could potentially slow down the country's economic growth over the next three years. Similarly, Njoroge (2020) explored the impact of Kenya's public debt on economic stability, highlighting the need for effective debt management strategies. Furthermore, Mohamedamin (2021) investigated the effect of national public debt on economic growth in Kenya, providing insights into the complex relationship between debt and economic performance. More recently, Machagua and Naikumi (2023) analyzed the effect of external public debt on private investments in Kenya, underscoring the importance of addressing the debt burden to stimulate domestic investment and economic development. These studies collectively demonstrate the pressing need to thoroughly examine the trajectory of Kenya's public debt and its potential implications for the country's future economic growth and stability.

The Autoregressive Integrated Moving Average (ARIMA) and Holt-Winters exponential time series models were selected for this study because, unlike other time series prediction models, they are capable of handling any series with or without the seasonality component (Box et al., 1970; Montgomery et al., 2008; Mutwiri, 2019). The little information available on forecasting public debt in Kenya and the inconsistency in the choice of a better prediction model between the ARIMA and the Holt exponential smoothing from previous studies necessitated the need for this research (Habibur Rahman et al., 2016; Mini et al., 2015; Omane-Adjepong et al., 2013; Makatjane and Moroke, 2016). This study presents a comprehensive approach to forecasting Kenya's public debt trajectory by evaluating two robust time series models: ARIMA and Holt-Winters exponential smoothing. While previous studies have explored debt forecasting for Kenya, they either focused on a single model or did not provide a rigorous comparative evaluation of different techniques.

This research thoroughly analyzes both ARIMA and Holt-Winters models, assessing their assumptions, goodness-of-fit, and predictive accuracy through out-of-sample forecasting. By benchmarking these two powerful forecasting approaches on an extensive historical debt dataset from Kenya, the study identifies the optimal model for reliably projecting the nation's future debt burden.

2. Materials and methods

2.1. Data sourcing and preprocessing

The public debt time series dataset spanning January 2001 to December 2021 was obtained from the open-access Central Bank of Kenya portal at www.centralbank.go.ke. This longitudinal secondary data covering the past two decades provided a robust historical base to forecast future debt trends.

The raw dataset underwent standard time series preprocessing and exploratory analysis using R statistical software version 4.1.2. Techniques like smoothing and stationarity transformations were applied to satisfy modeling assumptions. Time series plots visually assessed seasonality, trends, and outliers to inform suitable forecasting approaches.

2.2. Model fitting and selection

With the preprocessed data, various time series models were systematically fitted and evaluated to determine the optimal specification for accurate debt projection. The automated Akaike Information Criterion (AIC) metric guided the selection of the best ARIMA configuration by penalizing model complexity. In parallel, Holt exponential smoothing models with differing trend and seasonal components were tested.

2.3. Model specification

2.3.1. ARIMA model

According to Box et al. (1970) and Montgomery et al. (2008), the ARIMA model was first proposed by Box et al. (1970), formerly known as the Box-Jenkins methodology. ARIMA model uses past information and error terms when making forecasts. The ARIMA model is made up of three components, i.e., the differenced term (d), the Moving Average (MA) term, and the Autoregressive (AR) term. The longer the historical information, the better the prediction as the model progresses. Stationarity is a requirement for model fitting (Kinyili and Wanyonyi, 2021; Gechore et al., 2022). The ARIMA model is an extension of the ARMA model that includes at least one differencing term. The ARIMA (p, d, q) model is represented by the following equation:

$$\nabla^{\mathrm{d}} \mathrm{y}_{\mathrm{t}} = (1 - \mathrm{B})^{\mathrm{d}} \mathrm{y}_{\mathrm{t}}$$

where, $\nabla = 1 - B$ and B is the backward shift operator. The ARIMA model is generally written as.

$$\alpha_p (B)(1 - B)^d y_t = \beta_q (1 - B)\varepsilon_t. \quad (1)$$

A first-order differenced public debt series can be expressed in the form:

$$\Delta PD_t = (PD_t - PD_{t-1}) \quad (2)$$

where, PD_t is the public debt at time t. Therefore, the ARIMA (p, 1, q) model is expressed as

$$PD_t = \beta_0 + \phi_1 PD_{t-1} + \ldots + \phi_p PD_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}. \quad (3)$$

The Eq. 3 must first be stationary. If it is not, differencing is applied repeatedly until this condition is satisfied. The goal is to identify the best ARIMA (p,d,q) model for making predictions. For reliable forecasts, the ARIMA model relies on several important assumptions:

1. Stationarity: The ARIMA model assumes that the time series data is stationary, meaning that its statistical properties (such as mean, variance, and autocorrelation) remain constant over time. In this case, the original public debt data was non-stationary, so it was differenced twice to achieve stationarity before fitting the model.
2. Linearity: The ARIMA model assumes a linear relationship between the current value of the series and its past values, as well as between current and past forecast errors.
3. Normality of residuals: The ARIMA model assumes that the residuals (the differences between the actual and predicted values) follow a normal distribution.
4. Independence of residuals: The model assumes that the residuals are independent and not correlated with each other over time.

2.3.2. Adaptive Holt-winters forecasting model

This study implements an adaptive form of Holt-Winters exponential smoothing, a flexible time series prediction technique (Qader et al., 2021; Siddiqui et al., 2022). The methodology models data by decomposing it into evolving level and trend components and uses weighted averaging to forecast future values. The level represents the current series baseline, while the exponential trend captures the general direction and rate of change. The model assigns relative weights between past and recent data points to optimally balance responsiveness and smoothing. These data-driven smoothing constants dynamically adapt based on autocorrelations at each time step rather than using fixed empirically chosen values.

Critically, this adaptive approach accommodates intrinsic time series non-stationarity, where the underlying statistical properties shift gradually over time. This contrasts with most classical techniques that assume constancy. The evolving Holt-Winters framework circumvents this limitation by recursively tracking and projecting changes as they emerge. The Adaptive Holt-Winters Forecasting methodology is expressed as;

Level: $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (4)$
Trend: $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (5)$
Forecast: $F_{t+h} = L_t + hT_t \quad (6)$

where, Y_t is the observed value at time t L_t is the level at time t, T_t is the trend at time t, α is the smoothing parameter for the level, with $0 < \alpha < 1$, β is the smoothing parameter for the trend, with $0 < \beta < 1$, and h is the forecast horizon

The smoothing parameters α and β are constants that determine the weight given to the current observation versus the past observations. A higher value of α and β will give more weight to the recent observations, while a lower value will give more weight to the past observations (Djakaria and Saleh, 2021; Dassanayake et al., 2019). The Holt-Winters exponential smoothing model has a different set of assumptions:

- Level, Trend, and Seasonality: The Holt-Winters method assumes the time series can be decomposed into evolving level, trend, and seasonal components.
- Adaptive Smoothing: The Holt-Winters approach employs adaptive smoothing parameters that dynamically adjust based on the data.
- No Residual Autocorrelation: While the Holt-Winters model does not explicitly require normally distributed residuals, it assumes the residuals are independent and not autocorrelated.

2.4. Diagnostic test

The selected model is tested to determine whether it conforms to the specifications of stationarity. After fitting the model to the data and estimating parameters, a diagnostic test is performed on the fitted model. Model validation in time series is applicable when the parameters are estimated using the maximum likelihood estimation technique (Maurice et al., 2021; Gechore et al., 2022).

The normal Q-Q plot and bell-shaped histogram for the residuals were applied to test for the model normality. The Ljung Box test statistic was applied to test for the presence of serial correlation between the lags and determine if the residuals are independent and identically distributed.

2.5. Comparative evaluation

The chosen ARIMA and Holt models were benchmarked on out-of-sample predictive accuracy to identify the overall most reliable model for forecasting Kenya's future debt. Historical debt data from 2010-2021 was used to train both models, which were then used to generate forecasts for 2022-2023. These debt forecasts were compared against the actual debt figures from 2022-2023, which were recently released by the Central Bank of Kenya. The Root Mean Square Error (RMSE) was also applied to the model comparison. Between the two models, i.e., the model with the least errors was considered an optimal model for forecasting Kenya's public debt projections.

This rigorous predictive validity assessment focuses specifically on the models' abilities to forecast multiple future years in Kenya's debt time series. By comparing each model's multi-year forecasts to the true realized debt figures, the accuracy and reliability of the ARIMA and Holt models can be evaluated. Examining performance on this longer-range out-of-sample forecasting provides a robust evaluation for determining the preferable model for generating Kenya's future debt estimates. The model generates forecasts with the lowest deviation from the actual debt, which provides higher confidence in its applicability for the ongoing estimation of Kenya's debt trajectory.

3. Results and discussion

3.1. Time series plot

The time series plot for the national public debt in Fig. 1 shows an upward trend in the accumulated amount of money borrowed over the past two decades by the Kenyan Government.

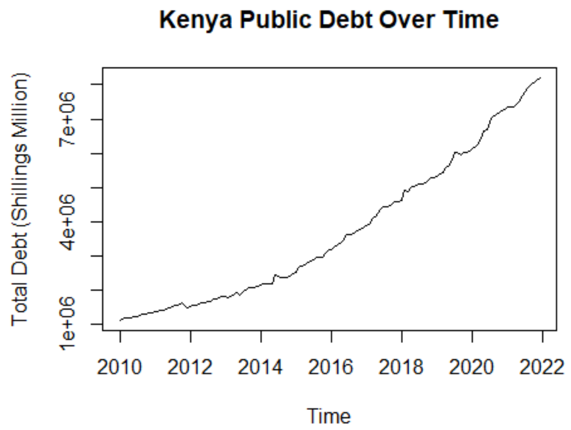

Fig. 1: Time series plot of total public debt

3.2. Checking for stationarity

It appears from the Augmented Dickey-Fuller test that the original national debt time series was non-stationary, as evidenced by the high p-value of 0.9667. The null hypothesis of a unit root could not be rejected, indicating non-stationarity. To remedy this, the time series was differenced twice to make it stationary, as shown in Fig. 2. The ndiffs () function in R software confirmed that 2 differences were required to achieve stationarity in this debt time series. Differencing is a common technique in time series analysis to convert a non-stationary series into a stationary one before fitting ARIMA or other models (Verma et al., 2021; Salles et al., 2019).

3.3. ARIMA model fitting

The $ARIMA(0,2,1)$, with no autoregressive term, second-order differencing, and first-order moving average, was chosen as the best-fitted model by the automated ARIMA function in R program using Akaike Information Criterion Key coefficients and performance indicators from the $ARIMA(0,2,1)$ model assessed goodness of fit. The only coefficient was -0.9428 for the moving average term with a 0.0222 standard error. The estimated residual variance was 3.33×10^9. Log-likelihood is optimized at -1758.84. AIC, which evaluates model quality based on goodness of fit and complexity, scored 3521.69 for the model, suggesting an excellent match for the differenced time series data.

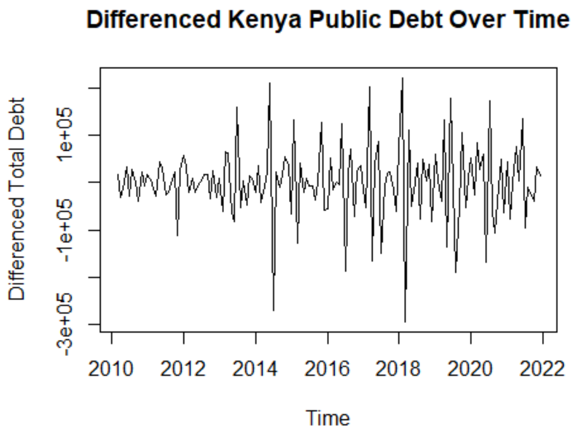

Fig. 2: Plot of differenced public debt

3.4. Holt-winters model fitting

The Holt-Winters additive method was used to fit the public debt time series while accounting for trend and seasonal cycles. Optimized smoothing parameters, which dictate the weights placed on the current versus historical data, included a high alpha of 0.9447963, assigning a 94% influence to the current observation. The beta trend parameter was estimated at 0.05340692. The seasonal smoothing parameter, gamma, was 0.2723258. These optimized coefficients stress the importance of current and seasonal effects for accurate future predictions. Additionally, the initial level and trend terms, a and b, respectively, establish the baseline debt and trajectory as the starting point for the exponential smoothing projections. By leveraging an adaptive model that emphasizes recent data and cyclic trends, the Holt-Winters technique provides data-driven forecasts of public debt while avoiding overfitting. The high alpha and seasonal gamma parameters exemplify how tuning the exponential smoothing model to the intrinsic data patterns enables reliable point estimates in the future.

3.5. Determining the optimal forecasting model for Kenya's public debt

The ARIMA and Holt-Winters models were compared to determine the most effective model for forecasting the trend of Kenya's public debt. Forecasting was done using both the ARIMA and Holt-Winters models for a period of two years, spanning from Jan. 2022 to Aug. 2023. The study aimed to compare the results of the two models with the actual existing data for the period between Jan. 2022 and Aug. 2023 and recommend the most effective model for forecasting the future trend of Kenya's public debt. The forecasting accuracy measures, such as the Mean Absolute Percentage

Error (MAPE) and the Mean Absolute Scaled Error (MASE), were also used to compare the forecasting accuracy for the above-mentioned models.

3.5.1. Forecast using ARIMA

Table 1 shows the forecasted public debt from Jan. 2022 to Aug. 2023 based on the ARIMA model with 80 and 95% confidence levels. Fig. 3 shows the plot of the ARIMA forecast for a period of two years spanning from Jan. 2022 to Aug. 2023.

3.5.2. Forecast using Holt-Winters

Table 2 shows the forecasted public debt from Jan. 2022 to Aug. 2023 based on the Holt-Winters model with 80 and 95% confidence levels. Fig. 4 shows the plot of Holt-Winters forecast for a period of two years spanning from Jan. 2022 to Aug. 2023.

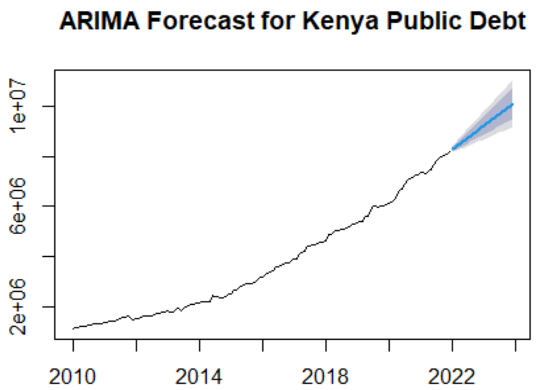

Fig. 3: plot of ARIMA forecast

Table 3 shows the forecasting accuracy measures that were considered while comparing the forecasting power between the ARIMA and the Holt-Winters model. According to Tofallis (2015), MAPE and MASE are the most effective accuracy measures in time series analysis since they minimize errors.

3.6. Comparative evaluation

The ARIMA model predicted public debt over a 20-month period, with forecasted values ranging from 8.28 trillion to 9.79 trillion. In comparison, the Holt-Winters model produced forecasts ranging from 8.29 trillion to 9.80 trillion. The forecast ranges for both models are very similar. For the lower limit, ARIMA forecasted 8.28 trillion, while Holt-Winters forecasted 8.29 trillion. The upper limits were 9.79 trillion for ARIMA and 9.80 trillion for Holt-Winters. These forecasted values closely match the actual debt, which ranged from 8.26 trillion to 10.53 trillion, as shown in Table 4, with a margin of error of 0.73 trillion.

Based on the accuracy measures, the MAPE was 1.173 and 1.329 for ARIMA and Holt-Winters, respectively. Also, the Mean Absolute Scale Error (MASE) was 0.065 and 0.074 for ARIMA and Holt-Winters, respectively. Considering the two accuracy measures, i.e., MAPE and MASE, the ARIMA and Holt-Winters models yield approximately equal errors with a margin of 0.01 for MASE and 0.16 for MAPE. This shows that the two models are effective and accurate in forecasting Kenya's public debt.

Table 1: ARIMA forecasts

Month/year	Point forecast	Low 80%	High 80%	Low 95%	High 95%
Jan 2022	8,285,808	8,211,857	8,359,759	8,172,710	8,398,906
Feb 2022	8,364,877	8,257,262	8,472,491	8,200,294	8,529,459
Mar 2022	8,443,945	8,308,400	8,579,490	8,236,647	8,651,243
Apr 2022	8,523,013	8,362,144	8,683,883	8,276,985	8,769,041
May 2022	8,602,082	8,417,322	8,786,842	8,319,516	8,884,648
Jun 2022	8,681,150	8,473,352	8,888,948	8,363,350	8,998,950
Jul 2022	8,760,219	8,529,901	8,990,537	8,407,978	9,112,460
Aug 2022	8,839,287	8,586,758	9,091,816	8,453,077	9,225,497
Sep 2022	8,918,355	8,643,784	9,192,926	8,498,435	9,338,275
Oct 2022	8,997,424	8,700,882	9,293,966	8,543,902	9,450,946
Nov 2022	9,076,492	8,757,979	9,395,006	8,589,368	9,563,617
Dec 2022	9,155,561	8,815,023	9,496,098	8,634,753	9,676,368
Jan 2023	9,234,629	8,871,975	9,597,283	8,679,998	9,789,260
Feb 2023	9,313,697	8,928,805	9,698,590	8,725,054	9,902,340
Mar 2023	9,392,766	8,985,487	9,800,045	8,769,887	10,015,645
Apr 2023	9,471,834	9,042,004	9,901,664	8,814,466	10,129,203
May 2023	9,550,903	9,098,341	10,003,464	8,858,770	10,243,036
Jun 2023	9,629,971	9,154,486	10,105,456	8,902,780	10,357,163
Jul 2023	9,709,040	9,210,430	10,207,649	8,946,482	10,471,597
Aug 2023	9,788,108	9,266,165	10,310,051	8,989,864	10,586,351

3.7. Discussion

The results of this study highlight the effectiveness of both the ARIMA and Holt-Winters exponential smoothing models in forecasting Kenya's public debt trajectory. The forecasted values from these two models are closely aligned with the actual debt figures, demonstrating their predictive accuracy. This finding corroborates previous studies that have successfully applied ARIMA (Filatova and Aiyedogbon, 2020; Dinh, 2020) and Holt-Winters models for forecasting economic time series, including public debt.

The ARIMA (0,2,1) model, with no autoregressive term, second-order differencing, and first-order moving average, emerged as the optimal specification based on information criteria. The significant moving average coefficient (-0.9428) indicates that past forecast errors play a crucial role in predicting future debt values. This finding aligns with Mutwiri's (2019) study, which employed ARIMA models for forecasting wholesale prices in

Kenya, highlighting the importance of accounting for past errors in time series predictions.

Concurrently, the Holt-Winters additive method effectively captured the trend and seasonal components present in Kenya's debt data. The high smoothing parameters for the level (α = 0.9447963) and seasonal component (γ = 0.2723258) underscore the model's adaptability to recent observations and cyclic patterns. This dynamic approach to exponential smoothing is consistent with Siddiqui et al. (2022) and Qader et al. (2021), who demonstrated the benefits of leveraging evolving level and trend components for accurate forecasting in various domains.

Table 2: Holt-Winters forecast

Month/year	Point forecast	Low 80%	High 80%	Low 95%	High 95%
Jan 2022	8,288,603	8,210,331	8,366,874	8,168,897	8,408,309
Feb 2022	8,376,534	8,266,104	8,486,964	8,207,645	8,545,423
Mar 2022	8,451,553	8,314,097	8,589,010	8,241,332	8,661,775
Apr 2022	8,506,050	8,344,014	8,668,086	8,258,237	8,753,863
May 2022	8,589,050	8,403,819	8,774,281	8,305,763	8,872,336
Jun 2022	8,717,080	8,509,499	8,924,661	8,399,612	9,034,548
Jul 2022	8,774,038	8,544,636	9,003,439	8,423,199	9,124,877
Aug 2022	8,855,024	8,604,132	9,105,916	8,471,318	9,238,731
Sep 2022	8,946,940	8,674,751	9,219,129	8,530,662	9,363,217
Oct 2022	9,009,424	8,716,037	9,302,812	8,560,727	9,458,122
Nov 2022	9,087,215	8,772,658	9,401,772	8,606,141	9,568,289
Dec 2022	9,154,248	8,818,498	9,489,998	8,640,763	9,667,733
Jan 2023	9,237,067	8,879,660	9,594,473	8,690,461	9,783,672
Feb 2023	9,324,998	8,946,266	9,703,730	8,745,777	9,904,218
Mar 2023	9,400,017	8,999,840	9,800,194	8,787,999	10,012,035
Apr 2023	9,454,514	9,032,753	9,876,275	8,809,487	10,099,541
May 2023	9,537,514	9,094,016	9,981,011	8,859,243	10,215,784
Jun 2023	9,665,544	9,200,144	10,130,944	8,953,776	10,377,311
Jul 2023	9,722,502	9,235,024	10,209,979	8,976,970	10,468,033
Aug 2023	9,803,488	9,293,750	10,313,225	9,023,912	10,583,064

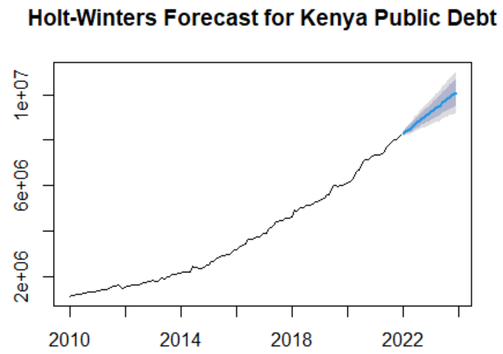

Fig. 4: plot of Holt-Winters forecast

Table 3: Accuracy measures

Time series models	MAPE	MASE
ARIMA	1.173	0.065
Holt-Winters	1.329	0.074

Table 4: Actual public debt data

Year	Month	Total debt
2023	8	10526430
2023	7	10416165.6
2023	6	10278673
2023	5	9686809.12
2023	4	9634853.13
2023	3	9,390,686.96
2023	2	9,261,276.43
2023	1	9,182,829.61
2022	12	9,145,982.65
2022	11	8,898,828.22
2022	10	8,745,663.83
2022	9	8,701,069.51
2022	8	8,663,204.08
2022	7	8,610,512.74
2022	6	8,579,108.53
2022	5	8,563,759.27
2022	4	8,470,377.84
2022	3	8,401,331.22
2022	2	8,339,183.76
2022	1	8,265,908.95

Both the ARIMA and Holt-Winters models yielded forecasts closely matching the actual debt figures, with a margin error of 0.73. This finding is comparable to the results of Omane-Adjepong et al. (2013), who reported similar accuracies when applying these models to forecast economic indicators in Ghana and software failures, respectively.

The accuracy measures, MAPE and MASE, further reinforced the reliability of the forecasts. The MAPE values of 1.173 for ARIMA and 1.329 for Holt-Winters are within the acceptable range for time series forecasting. Similarly, the MASE values of 0.065 and 0.074 for ARIMA and Holt-Winters, respectively, indicate a low degree of forecasting errors compared to the naïve method, aligning with the findings of Tofallis (2015) on the effectiveness of MASE as an accuracy metric.

The negligible difference in errors between the two models suggests that both ARIMA and Holt-Winters are suitable for forecasting Kenya's public debt. This convergence of results is consistent with the findings of Makatjane and Moroke (2016) and Mini et al. (2015), who reported comparable performance between ARIMA and Holt-Winters models in forecasting applications across different domains.

Overall, the study's findings contribute to the growing body of literature on public debt forecasting and reinforce the applicability of ARIMA and Holt-Winters models in this context. By providing accurate projections of Kenya's future debt burden, the results offer valuable insights for policymakers and economic planners to develop effective strategies for sustainable debt management and fiscal reforms.

4. Conclusions

This study investigated the efficacy of the ARIMA and Holt-Winters exponential smoothing models in forecasting Kenya's public debt trajectory over a 20-month period. By rigorously evaluating the forecasting accuracy and comparing the projected values against the actual debt figures, the research provides compelling evidence for the suitability of these time series models in predicting Kenya's future debt burden. The ARIMA (0, 2, 1) specification, characterized by second-order differencing and a significant moving average component, effectively captured the underlying patterns in the debt data. Concurrently, the Holt-Winters additive method demonstrated its ability to adapt to recent observations and seasonal cycles, leveraging optimized smoothing parameters for the level, trend, and seasonal components.

Notably, both models yielded forecasts that closely aligned with the actual debt values, exhibiting a margin error of only 0.73. This remarkable predictive accuracy is further substantiated by the low MAPE and MASE values, which are well within the acceptable ranges for time series forecasting. The negligible difference in error metrics between the two models suggests that they perform comparably in forecasting Kenya's public debt. The convergence of results from the ARIMA and Holt-Winters models not only reinforces their individual robustness but also highlights their complementary strengths in capturing diverse aspects of the debt time series. While ARIMA excels in modeling autocorrelations and error components, Holt-Winters effectively captures evolving trends and seasonal patterns, offering a comprehensive forecasting approach when applied in tandem.

This study makes a significant contribution to the literature by comprehensively evaluating and benchmarking two powerful time series forecasting models specifically for the context of public debt in Kenya. By demonstrating the predictive accuracy and reliability of these models, the research provides valuable insights and tools for policymakers, economic planners, and fiscal authorities to develop informed strategies for sustainable debt management and fiscal reforms.

The findings of this study open up avenues for further research, such as exploring the integration of exogenous economic variables or investigating the impact of different debt components (domestic vs. external) on forecasting accuracy. Additionally, extending the forecasting horizon and regularly updating the models with new data can enhance their predictive capabilities and ensure their continued relevance in guiding Kenya's fiscal policies. In conclusion, this research firmly establishes the ARIMA and Holt-Winters models as robust and accurate forecasting tools for Kenya's public debt trajectory. Their successful application reinforces the importance of leveraging advanced time series techniques in economic forecasting and underscores the potential for similar methodologies to be applied in other developing nations facing public debt challenges.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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