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Original Research

Modelling Consumer Price Index in Tanzania: Holt Winter's Approach

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Abstract

Consumer price index (CPI) is a socioeconomic statistic that tracks changes over time in the average price of consumer goods and services such as household purchases of fuel, transportation, food and so on that consumers buy, use, or pay for. The purchasing power of everyone is impacted by rising costs, especially if salaries stay the same. Our ability to purchase more things with our TZS reduces when the CPI increases more quickly than earnings, which has an impact on our cost of living. The aim of this study is to use the CPI monthly data from IMF website for the period from Jan 2010 to Dec 2022 to develop a forecasting model by using Holt Winter's approach. Holt Winter's model based on four equations and popularly known as Triple exponential smoothing is commonly used in forecasting data with trends and seasonality. Holt Winter's model is composed of four equations relating to level, trend, seasonal and forecast. The results revealed that the Holt winter's model with smoothing parameters, 0.9 for level, 0.12 for trend, and 0.03 for seasonal was the best model in forecasting Consumer Price Index. The CPI for Tanzania is predicted for the next eighteen months and it has been observed that the trend of CPI is likely to increase in the next eighteen months.

Keywords: CPI, forecasting, IMF, model.

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Introduction

Consumer price index (CPI) is a socioeconomic statistic that tracks changes over time in the average price of consumer goods and services such as household purchases of fuel, transportation, food and so on that consumers buy, use, or pay for (Shinkarenko et al., 2021). The purchasing power of everyone is impacted by rising costs, especially if salaries stay the same. Our ability to purchase more things with our shillings reduces when the CPI increases more quickly than earnings, which has an impact on our cost of living (Zhang, 2023). The CPI is a crucial economic indicator since it serves as a potential indicator of future economic issues. Rising inflation has an impact on the central bank's policy rate and raises lending interest rates. Knowing the CPI's long-term trends is crucial for creating a strong and resilient economy (Iftikhar, 2013).

Forecasting CPI is a crucial field of study since it aids in understanding the trend of the consumer price index and how it influences several financial decisions. Investors desire accurate inflation estimates since the returns on stocks and bonds completely depend on the path of inflation (Lidiema, 2017). Businesses use inflation estimates to plan their production schedules and establish prices for their goods and services. When precise forecasting results aid in the development of future government policies, forecasting becomes an important tool in the corporate sphere (Corpin et al., 2023). For a number of economic factors, including efficiency, financial markets, and monetary policy, it is critical to accurately estimate the change in the CPI (Wanto et al., 2018). Furthermore, the general public, decision-makers, and academics will place a great deal of importance on developing a reliable and precise CPI forecasting model (Rohmah et al., 2021).

The rising CPI indicates that the cost of goods and services is rising. Without forecasting CPI, it is impossible to predict future inflation rates, which makes it difficult for lenders to set loan terms and is bad for the economy. This would result in customers having less purchasing power. Additionally, consumers with lower incomes must spend a larger percentage of their income on basic necessities. Furthermore, the trade-off between unemployment and inflation may suffer in the public and private sectors. In this matter, predicting consumer price index in Tanzania is crucial for avoiding these negative effects. Therefore, the objective of this research is to forecast consumer price index in Tanzania by using a double exponential model.

Statement of the problem

Autoregressive Integrated Moving Average(ARIMA) model is widely applied in econometrics and time series analysis. While this model offers valuable insights and have proven effective in many applications, it has certain limitation and challenges. It is unable to deal with complex dynamics or nonlinear interactions, such as rapid shocks or regime changes in the time series (Ospina et al., 2023).

Researchers and practitioners often address these limitations by using different models, exploring hybrid approaches, or incorporating additional techniques to improve forecasting accuracy and capture the complexities of real-world data. Exponential smoothing models are relatively robust against isolated outliers or temporary shocks in the data. The weighted averaging nature of exponential smoothing assigns less weight to extreme observations, which helps dampen the impact of outliers on the forecasts. This study aims to address this gap by applying exponential smoothing models to forecast consumer price index in Tanzania.

Literature Review

Numerous Studies have been carried out for the CPI forecast analysis. The ideal model for Consumer price index prediction, however, has not yet been agreed upon by researchers.

Shinkarenko et al., (2021) in his study examined the trend of the consumer price index in Ukraine for the period from January 2010 to September 2020. He tried to model the behavior of the consumer price index and forecast for the next months, two types of models were used: the additive ARIMA*ARIMAS model, better known as the model of Box-Jenkins and the exponential smoothing model with the seasonality estimate of Holt-Winters. As a result of using the STATISTICA package, the most adequate models were built, reflecting the monthly dynamics of the consumer price index in Ukraine. The inflation forecast was carried out on the basis of the Holt-Winters model, which has a minimum error.

In order to develop a forecasting model, (Arindam Banerjee, 2021) utilized monthly time series data on Consumer Price Index (CPI) in India and the Box-Jenkins auto regressive integrated moving average (ARIMA) technique. The ARIMA (1,1,5) model was identified in this study as the best one for CPI prediction in India. The model was evaluated using monthly data from the first of January 2019 to the first of January 2020. The Consumer Price Index is predicted to grow at a rate of 6.67% by the model, whereas the actual CAGR of the CPI during the validation period was 6.68%.

Nnamdi et al. (2022) compared some time series models using the monthly Consumer Price Index (CPI) of consumer goods in Nigeria. The data used for the study was the monthly CPI of all items from January 2009 to January 2021, sourced from the National Bureau of Statistics (NBS). The CPI was computed using November 2009 as the base period. The study seeks to obtain the time series model that best fits the data to make more accurate forecasts from the series. Of the four models considered in the study, the double exponential smoothing model was found to be the best model for the monthly CPI and was therefore employed to make an 18-month forecast of the series.

A study on inflation was conducted in Kenya using 180 monthly data values by Uwilingiyimana et al. (2015). The findings showed that the ARIMA (1, 1, 12) model was better able to anticipate the data based on the stationarity test and historical trends than the GARCH (1, 2) model. He continued by showing that, when compared to past forecasting methods, the model generated the best results and markedly improved estimate and forecasting accuracy.

Molebatsi & Raboloko (2016) applied an autoregressive integrated moving average for modeling consumer price index (CPI) in Botswana. He enhanced the model by incorporating the generalized autoregressive conditional heteroscedasticity

(ARCH/GARCH) model that accounts for volatility in the time series. In the course of analysis, CPI was predicted using the two models, ARIMA (1, 1, 1) and ARIMA (1, 1, 1) + GARCH (1, 2), and the predicted CPI was compared to the actual CPI. Since their 95 percent confidence intervals covered the real CPI, both models performed well in terms of forecasting. When error terms were examined for normality, minor differences were discovered that supported the inclusion of the ARCH/GARCH components. The study also demonstrates that CPI volatility in Botswana was low, as evidenced by the low values of its ARCH/GARCH components.

In the case of Tanzania, Nyoni (2019) used ARIMA to forecast the inflationary trend. He discovered that the ARIMA models (1, 1, 2) had a better forecasting accuracy. According to Ngailo et al. (2014) who studied inflation using time series models with data from January 1997 to December 2010, the GARCH (1, 1) model was the most useful for forecasting inflation in Tanzania.

Research Methodology

Research design

Longitudinal research design is a research approach that involves studying the same sample or group of individuals over an extended period. It aims to examine changes, trends, or developments that occur within the sample over time, allowing researchers to understand the dynamic nature of various phenomena (Ali & Mahgoub, 2020). In addition, longitudinal research designs provide valuable insights into the dynamics of various phenomena over time, offering a rich understanding of individual and group-level changes, development, and causal processes (Kelikume & Salami, 2014).

Data

This study will utilize monthly consumer price index data for the period from January 2010 to December 2022 from the IMF website. R software was used for the analysis and model building.

Single exponential Smoothing

Single exponential smoothing is a time series forecasting method used to make predictions based on the weighted average of past observations. It is a simple and widely used technique for forecasting future values in a time series, especially when the data does not exhibit complex patterns or seasonality (Prapcoyo & As’ad, 2022).

The single exponential smoothing method assigns exponentially decreasing weights to past observations, with the most recent observations given more weight than the older ones (Lidiema, 2017). The formula for calculating the forecast using single exponential smoothing is shown by (1) as:

$$F(t+1) = \alpha Y(t) + (1 - \alpha) F(t) \tag{1}$$

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Where: F(t+1) is the forecast for the next time period (t+1), Y(t) is the actual observation at time t, F(t) is the forecast for the current time period (t) and α is the smoothing factor or smoothing parameter ($0 < \alpha < 1$).

The smoothing factor, α, determines the weight given to the most recent observation versus the previous forecast. A higher α places more emphasis on recent data, making the forecast more responsive to recent changes. Conversely, a lower α gives more weight to historical data, making the forecast more stable and less responsive to recent fluctuations (Muhammed et al., 2019).

Double exponential smoothing

Double exponential smoothing approach, also known as Holt's method, is an extension of single exponential smoothing that incorporates trend information in addition to level (or average) information. It is a popular time series forecasting technique used to make predictions for data with a trend but no seasonal patterns (Mohamed, 2020).

In double exponential smoothing, there are two components: the level component (denoted as L) and the trend component (denoted as T). The level component represents the average value of the time series, while the trend component captures the direction and rate of change of the series (Nnamdi et al., 2021). The forecast at time t+1 is calculated using (2), (3) and (4):

Level equation:

$$L(t) = \alpha Y(t) + (1 - \alpha) (L(t-1) + T(t-1)) \tag{2}$$

Trend equation:

$$T(t) = \beta(L(t) - L(t-1)) + (1 - \beta) T(t-1) \tag{3}$$

Forecast equation:

$$F(t+k) = L(t) + k(T(t)) \tag{4}$$

Y(t) is the actual observation at time t, L(t) is the level component at time t, T(t) is the trend component at time t, α is the smoothing factor for the level component ($0 < \alpha < 1$), β is the smoothing factor for the trend component ($0 < \beta < 1$), k is the number of periods ahead for the forecast.

Double exponential smoothing technique provides more accurate forecasts than single exponential smoothing for time series data with trends. However, it still assumes that the trend is linear and does not handle seasonal patterns (Ali & Mahgoub, 2020). For data with complex trends or seasonal variations, more advanced methods such as triple exponential smoothing or seasonal methods like Holt-Winters can be used (Lidiema, 2017).

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Triple exponential smoothing

Triple Exponential Smoothing (TES) is used to forecast time series data that exhibit trend and seasonality. It consists of three components: the level component, the trend component, and the seasonal component. The method uses three smoothing factors: α for the level component, β for the trend component, and γ for the seasonal component (Prapcoyo & As'ad, 2022). The formulas for calculating the forecast, level, trend, and seasonal components in Triple Exponential Smoothing are as represented as follows:

For the additive model, the equations are shown by (6), (7), (8) and (9);

Level equation:

$$L(t) = \alpha\ (Y(t) - S(t-L)) + (1 - \alpha)\ (L(t-1) + T(t-1)) \quad (5)$$

Trend equation:

$$T(t) = \beta\ (L(t) - L(t-1)) + (1 - \beta)\ T(t-1) \quad (6)$$

Seasonal equation:

$$S(t) = \gamma\ (Y(t) - L(t)) + (1 - \gamma)\ S(t-L) \quad (7)$$

Forecast equation:

$$F(t+k) = L(t) + k\ (T(t)) + S(t-L+k) \quad (8)$$

For the multiplicative model, the equations are (9), (10), (11) and (12);

Level equation:

$$L(t) = \alpha\ (Y(t)/S(t-L)) + (1 - \alpha)\ (L(t-1) + T(t-1)) \quad (9)$$

Trend equation:

$$T(t) = \beta\ (L(t) - L(t-1)) + (1 - \beta)\ T(t-1) \quad (10)$$

Seasonal equation:

$$S(t) = \gamma\ (Y(t)/L(t)) + (1 - \gamma)\ S(t-L) \quad (11)$$

Forecast equation:

$$F(t+k) = (L(t) + k\ (T(t)))\ S(t-L+k) \quad (12)$$

Y(t) is the actual observation at time t, L(t) is the level component at time t, T(t) is the trend component at time t, S(t) is the seasonal component at time t, L is the length of the seasonal cycle, k is the number of periods ahead for the forecast and α, β, and γ are the smoothing factors for the level, trend, and seasonal components, respectively.

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Triple Exponential Smoothing technique is a more advanced method than double exponential smoothing as it takes into account both trend and seasonality. It is particularly useful for forecasting data with recurring seasonal patterns (Efrilia, 2021).

Mean Absolute Error

Mean Absolute Error (MAE) is a commonly used metric to evaluate the accuracy of a forecasting model. It measures the average absolute difference between the predicted values and the actual values. The lower the MAE, the better the model's performance (Aabeyir, 2019). The absolute errors for each data point are obtained by subtracting the predicted value from the actual value and taking the absolute value as follows

$$MAE = (1/n)\ \Sigma\ (|A - P|)$$

Where n is the total number of data points, A is the actual values and P is forecasted values.

Mean Squared Error

Mean Squared Error (MSE) is another commonly used metric to evaluate the accuracy of a forecasting model. It measures the average of the squared differences between the predicted values and the actual values. The lower the MSE, the better the model's performance (Prapcoyo & As’ad, 2022).

$$MSE = (1/n)\ \Sigma\ ((A - P)\ \text{^}2$$

n is the total number of data points; A is the actual values and P is forecasted values. obtain a metric that is more interpretable and in the same unit as the original data, you can consider taking the square root of the MSE, which results in the Root Mean Squared Error (RMSE) (Ali & Mahgoub, 2020). The RMSE is often used as an alternative to the MSE and provides a measure of the average deviation in the original unit of the data.

Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a commonly used metric to evaluate the accuracy of a forecasting model, particularly when dealing with relative errors. It measures the average percentage difference between the predicted values and the actual values. The lower the MAPE, the better the model's performance (Nnamdi et al., 2021). Divide the sum of absolute percentage errors by the total number of data points to obtain the mean:

$$MAPE = (1/n)\ \Sigma\ (|A - P|\ /\ A) * 100$$

n is the total number of data points; A is the actual values and P is forecasted values. The MAPE provides a measure of the average percentage deviation between the predicted and actual values. It is especially useful when the magnitude of the errors relative to the actual values is important for analysis (Mia, 2019).

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Results

The trend of consumer price index

The historical CPI index data is plotted in Figure 1 from January 2000 to December 2022. Given that the series has an overall increasing trend and a seasonal component, the triple exponential model is appropriate since it captures the trend and seasonality that exists in the CPI index data. Shows

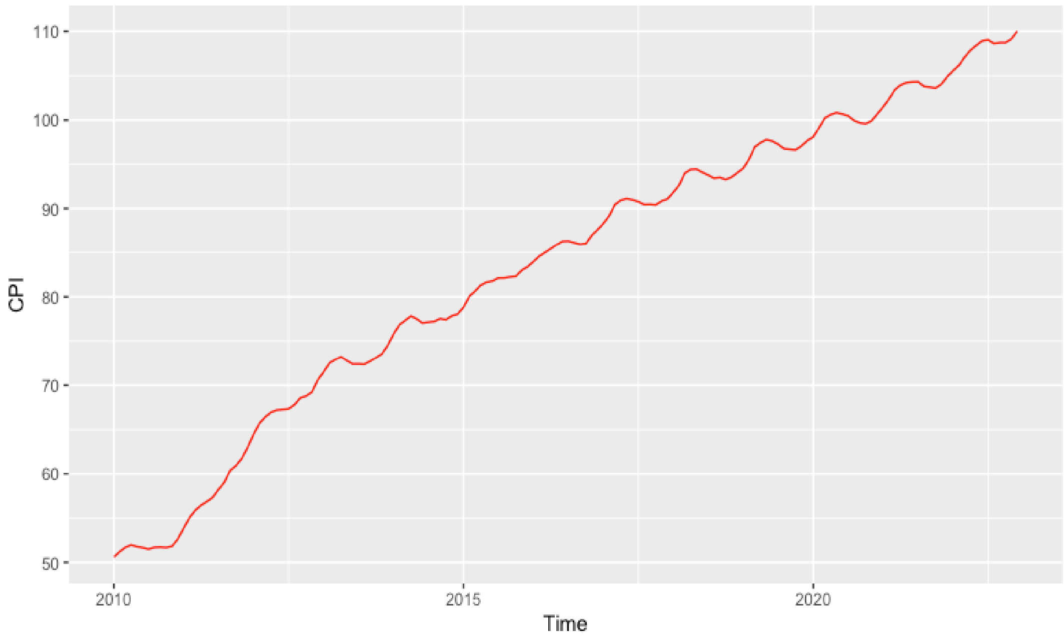

Figure 1: Consumer Price Index

In this case, three equations have to be fitted, level, trend and seasonal with α, β and γ as smoothing parameters respectively.

Selection of smoothing parameters

In order to choose the best smoothing parameters, the trial-and-error method was used. In this procedure of choosing a smoothing parameter, 0.9, 0.12 and 0.03 were determined to be the optimum smoothing parameters for α, β and γ respectively as shown in table 1.

The best model was chosen based on the lowest values generated by various measurements of accuracy chosen, which are MAE and RMSE, as shown in table 1. This model, which can be used to estimate the future values, has values of 0.9 for level, 0.12 for trend, and 0.03 for seasonal. These parameters had a small error (RMSE (0.3034468), MAPE (0.3011188)) when compared to other smoothing constants.

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Table 1. Triple exponential smoothing parameters

Smoothing constant, α (Level)	Smoothing constant, β (Trend)	Smoothing constant, γ (Seasonal)	RMSE	MAPE
0.7	0.12	0.01	0.3429642	0.3435283
0.8	0.15	0.03	0.3185002	0.3166101
0.95	0.1326	0.0418	0.3044733	0.3163559
0.7	0.15	0.02	0.3403631	0.3422364
0.8	0.1	0.01	0.3223489	0.3209479
0.9	0.12	0.03	0.3034468	0.3011188
0.7	0.1	0.03	0.3501002	0.3508799
0.8	0.12	0.02	0.3208185	0.3189957
0.9	0.1	0.02	0.305141	0.3013425

Table 2 displays the predicted values for the upcoming 18 months, which are totally inflated by their convergence and indicates the overall trend.

Table 2. CPI predictions for the next 18 months

Month	Point forecast	Lo 95	Hi 95
Jan 2023	110.9050	110.2750	111.5349
Feb 2023	111.9801	111.0480	112.9123
Mar 2023	112.9092	111.6997	114.1187
Apr 2023	113.4644	111.9837	114.9451
May 2023	113.6329	111.8802	115.3855
Jun 2023	113.5368	111.5084	115.5653
Jul 2023	113.5014	111.1916	115.8112
Aug 2023	113.3245	110.7270	115.9220
Sep 2023	113.5484	110.6563	116.4406
Oct 2023	113.6290	110.4350	116.8230
Nov 2023	114.2010	110.6979	117.7041
Dec 2023	114.9209	111.1013	118.7405
Jan 2024	115.8159	111.6621	119.9696
Feb 2024	116.8910	112.4069	121.3752
Mar 2024	117.8201	112.9981	122.6420
Apr 2024	118.3753	113.2083	123.5422
May 2024	118.5438	113.0246	124.0630
Jun 2024	118.4477	112.5693	124.3262

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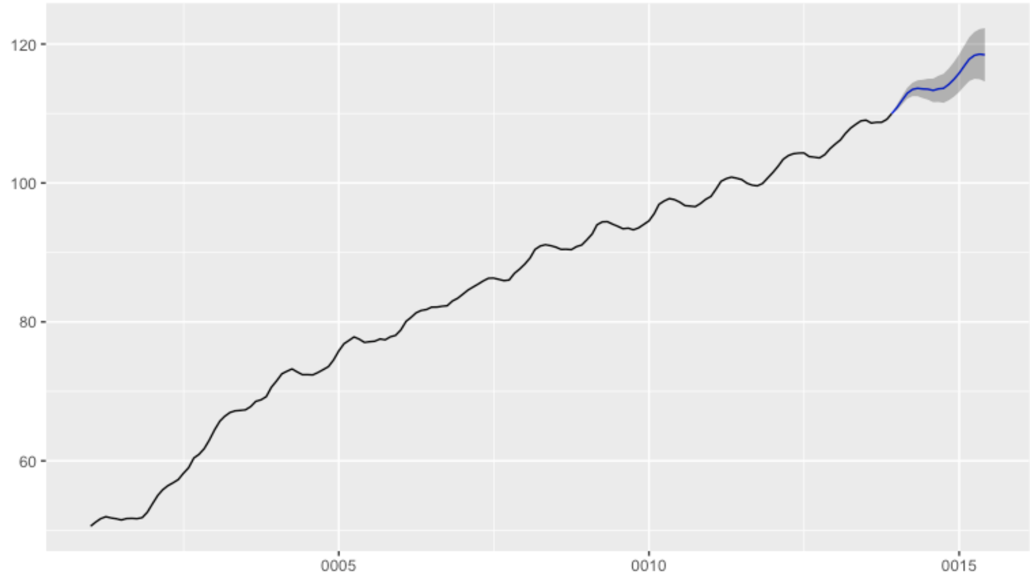

Figure 2. Forecasted CPI index values

The predicted values are shown in Figure 2 for the next 18 months, and it is clear that the Tanzania CPI will tend to rise in a positive direction.

Discussion

According to previous research, Nyoni (2019) used the ARIMA model to accurately estimate CPI, whereas Ngailo et al. (2014) determined that the GARCH model was the best one for forecasting the CPI and rising prices. Based on the internal consistency of the smoothing model, which is illustrated by a low mean square error, the Holt Winter's approach provides a better forecast. The accuracy of the prediction model is demonstrated by this study by the predicted values, which are much closer to the actual values. The findings of this study are consistent with prior studies conducted by Aabeyir (2019) and Efrilia (2021). They discovered that compared to other forecasting approaches, double or triple exponential smoothing can produce more accurate findings.

Conclusion and Recommendation

Conclusion

Based on the results and discussion in this study, Holt Winter's approach is the most suitable model to forecast the CPI values in the short and long runs. According to Holt Winter's forecasting model, the CPI is likely to rise over the next 18 months. Prediction models typically work better over shorter time spans and their accuracy declines over time because, it is difficult to anticipate human behavior for the long run. This limitation exists naturally in all mathematical models of human consumption behavior. The results revealed that the holt winter's model with smoothing parameters 0.9 for level, 0.12 for trend, and 0.03 for seasonal was the best model in forecasting Consumer Price Index

Recommendation and area for further studies

The current study has important implications for real life as well. The government should employ fiscal measures like interest rate ceilings, lower government expenditure, and sustainable taxes to manage inflation since the Consumer Price Index (CPI) is rising.

To enhance the forecast of the consumer price index, future research may examine hybrid models like SARIMA and machine learning algorithms such as Support Vector Regressor (SVR) and Random Forest Regressor (RFR). The SVR model includes more predictors of consumer price index like interest rates and taxes to account for additional variability in the commodity prices.

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