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# Modeling inflation rate factors on present consumption price index in Ethiopia: threshold autoregressive models approach

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## Abstract

**Background** Inflation is the industrious and non-stop ascent in the overall prices of any given commodity in an economy. During the global food crisis, Ethiopia experienced an unprecedented increase in inflation ranked the highest in Africa. It is among the most macroeconomic variable described nonlinear behavior.

**Objective** The main purpose of this study was intended to modeling inflation rate factors on present consumption price index (CPI) in Ethiopia: using the threshold autoregressive (TAR) models.

**Methods** The study was utilized the secondary data collected from monthly data of CPI for inflation rate from January 1994 to December 2020 which was obtained from central statistical Agency. The forecast was applied between the nonlinear and linear ARMA models using different techniques. The unit root test of Dickey–Fuller test was made for each variables and applied lag length transformation for the variables that had unit root. A threshold autoregressive models was utilized for data handling technique using least square estimation.

**Results** The results showed that monthly rate of inflation was characterized a non-constant mean and an unstable variance. The outcome of Tsay tests was revealed that non linearity of CPI and SETAR(2,4,4) had the smallest value of AIC under this study. The forecasting performance comparison results were showed that the nonlinear SETAR model outperform the linear ARMA models. Moreover, the out-of-sample forecast indicates that the CPI of inflation has almost a constant trend. The in-sample forecast using the best-fit asymmetric for the SETAR(2,4,4) model the CPI series exhibits an upward trade until 2012; decreases until 2011; slightly increase up to 2018 and then decrease at the end of the study period.

**Conclusion** The superiority in performance of nonlinear models was attributed to their ability to capture the stochastic nature of the monthly rates as evident in the pattern of the forecast errors. The investigators are recommended that using TAR models policy makers can be able to capture the price volatility persistence and also forecasting can be made.

**Keywords** Inflation rate, CPI, Stationary, Nonlinear models, TAR models, Ethiopia

## Introduction

Inflation is the persistent and continuous rise in the general prices of commodities in an economy [1]. Maintenance of price stability continues to be one of the main objectives of monetary policy for most countries in the world today [1]. In recent years, rising inflation has become one of the major economic challenges forecasting most countries in the world, especially, developing

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countries. Therefore, the uncertainty with regard to future inflation rate needs to be addressed by the policy makers so as to formulate effective monetary, fiscal and other policies [2].

There are different types of inflation such as demand pull inflation caused by increase in demand due to increased private and government spending. There is also cost push inflation which is caused by reduced supplies due to increased prices of inputs, and structural inflation caused by deficiencies in certain conditions in the economy such as backward agricultural sector that is unable to respond to people's increased demand for food, and inefficient. An increase in aggregate demand without a corresponding increase in supply, results in an inflationary gap which induces increase in prices [3]. Inflation reduces savings, pushes up nominal interest rates, dampens investment, and leads to depreciation of the currency and in extreme cases it can lead to the breakdown of a nation's monetary system and affects everyone in the economy.

The beginning of the 21th century was marked by low and stable inflation across the developed world and reduced inflation in the developing world. Study into the effects of these movements in commodity. The NBE in 2019 data reveals that average annual inflation rate for the years before 2004 was 2.5% but the yearly average after 2004 reached 15.1% prices on domestic inflation has generally been restricted to a small sample of typically advanced countries, owing principally to a lack of readily available data. The most recent CSA in 2019 commodity weights were available for individual commodity at regional level and aggregate weights were constructed for baskets of commodities.

Some countries in Africa have managed to maintain relatively stable prices, while others have seen prices rising rapidly. One of the most affected countries is Ethiopia which, with the exception of Zimbabwe and small Island economies, has had the strongest acceleration in food price inflation during recent years. Inflation rate has a serious negative effect on the growth of one country's economy especially in Ethiopia, if inflation has a double digit of an annual growth [4]. Sound and productive level of inflation, as noted by [5] is certainly regarded as a repercussion of fiscal prudence and essential criteria for the attainment of a sustainable level of growth and development.

Forecasting the accurate inflation help better financial planning improvements in both the corporate and private sectors. It is also important for banking sector in order to keep their investments profitable that help banks achieve their operating capital requirements. Furthermore, it can give investors information about whether or not to invest in the bond market, as fixed rate bonds lose value in periods of inflation. This simulation is adopted in every field of study so as to make the decision-making activity more effective and accurate [6]. Keeping in view this significance of forecasting, the economic policy makers require certain models that enable them to look into the future and draw up the policies with precision and certainty. One of the most significant and uncertain economic elements is inflation that needs to be watched, analyzed and predicted before it gets too late for the policy makers [7].

The overall inflation in Ethiopia is closely associated with agriculture and food in the economy that has an impact on domestic food prices. This inflation period was characterized by shortages of key consumer goods that resulted into black market sales of goods with government controlled prices [8]. According to [9], shows a better performance linear time series (ARIMA) model. Thus, this study aimed to fill this gap of information by estimating threshold autoregressive model for inflation rate in Ethiopia based on data inflation collected from January 1994 to December 2020 which was monthly data obtained from CSA. In view of this study conducted on modeling and forecasting CPI for inflation rate with different nonlinear time series models such as SETAR model, which is one of the TAR group modeling, shows a better performance than many other linear and nonlinear modeling. The study aimed to apply nonlinear models is not influenced by structural breaks or dynamic behavior of time series data that can adequately accommodate either structural instability or regimes than the class of linear models.

Ref [10] Aimed to find a suitable method for forecasting the inflation rate and evaluated the performance of nonlinear models for forecasting the financial time series data found that nonlinear models, such as threshold autoregressive (TAR) and smooth transition autoregressive (STAR) models, performed better than linear models in the case of US and UK asset returns. However, the asymmetric behavior of inflation rate was modeled using nonlinear time series model. The TAR is capable of capturing the possible nonlinear and non-stationary behavior in the inflation rate.

Thus, the main purpose of this study was intended to modeling inflation rate factors on present consumption price index in Ethiopia: using the application of threshold autoregressive models. To the end of this, the investigators were forwarded about this models and forecasting the causes and consequences of inflation rate in Ethiopia.

## Methods and materials

### Source of data

The data were collected from secondary source on macroeconomic variables such as consumer price index (CPI) and inflation rate were obtained from central statistical Agency (CSA) during the period of January 1994 to December 2020, it was measured in monthly data. The data of CPI were collected from the purpose of monitor changes in price movements and to observe its effect on their program implementation and policy decisions (CSA, 2010).

### Variables considered under the study

Dependent Variable (Inflation Rate (IR)): is the annual percentage change in consumer price index. Independent Variable (Consumer Price Index (CPI)): is a measures change in the prices of goods that households consume.

### Methods of data analysis

Descriptive Statistics and econometric models were employed for analyzing the data were utilized in this study. A graphical representation of autocorrelation function (ACF) and partial autocorrelation function (PACF) also used to give hints about autoregressive and moving average characteristics of the time series. The nonlinear econometric model such as threshold autoregressive model (TAR), self-exiting threshold autoregressive (SETAR), smooth threshold autoregressive model (STAR) and logistic smooth threshold autoregressive model (LSTAR) was used to modeling and forecasting inflation rate in Ethiopia.

Test of Stationary: The concept of stationary of a stochastic process can be visualized as a form of statistical equilibrium the statistical properties such as mean and variance of a stationary process do not depend upon time [11].

Unit Root Test: A series is said to be stationary if the mean and auto co-variances of the series do not depend on time [12].

Augmented Dickey–Fuller (ADF) Test: The first and simplest test for unit root non-stationary. It comes in several variants depending on whether allow a non-zero constant and/ or a deterministic trend.

### Linear time series models

It was proposed an autoregressive moving-average (ARMA) model that reduces the number of parameters by combining both the AR and MA models. The AR(p) was model as follows:

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t \quad (2.1)$$

where observations of the time series are denoted by the y's, $\varepsilon_t$ is the random error at time.

$$y_t - \varphi_1 y_{t-1} - \ldots - \varphi_p y_{t-p} = \alpha_t + \theta_1 \alpha_{t-1} + \ldots + \theta_q \alpha_{t-q} \quad (2.2)$$

where $\{\alpha_t\}$ is a white noise process with $E(\alpha_t) = 0$ and $\nu(\alpha_t) = \delta^2 u$[13].

### Nonlinear time series models

It has two groups according to the assumed switching behavior of the variable under consideration between different regimes. Nonlinear models should also be considered for better time series analysis and forecasting [14].

### Threshold autoregressive (TAR) models

It is quite complex which involves several computing intensive stages and there were no diagnostic statistics available to assess the need for a threshold model for a given data set [15]. The TAR (1) is:

$$x_t = \begin{cases} \alpha^{(1)} x_{t-1} + \varepsilon_t, x_{t-1} < d \\ \alpha^{(2)} x_{t-1} + \varepsilon_t, x_{t-2} + \geq d \end{cases} \quad (2.3)$$

where $\alpha^{(1)}$ and $\alpha^{(2)}$ are the coefficient in lower and higher regime, respectively, which needs to be estimated. $x_t = \alpha^{(i)} x_{t-1} + \varepsilon^{(i)}$ If, $x_{t-1}$ lies in $R_i = (i = 1, \ldots, k)$ Where $R_1, \ldots, R_k$ are given set real numbers. General nonlinear first order model:

$$x_t = \lambda(x_{t-1} + \varepsilon_t) \quad (2.4)$$

where $\lambda(x)$ is some general function of x the p order model TAR (p) is:

$$x_t + \alpha_1^{(i)} x_{t-1} + \ \ldots \ + \alpha_p^{(i)} x_{t-p} + \varepsilon^{(i)} \quad (2.5)$$

If $x_{t-1}, \ldots, x_{t-p}$ lies in $R^i$ and $R^j$, i = 1,..., k is given region of p dimensional space [16].

$$y_t = \begin{cases} \alpha_{10} + \alpha_{11} y_{11} + \ldots + \alpha_{1p} y_{1p} + \varepsilon_{1t}, if, \gamma_{t-d} > \tau \\ \alpha_{20} + \alpha_{21} y_{11} + \ldots + \alpha_{2p} y_{1p} + \varepsilon_{2t}, if, \gamma_{t-d} < \tau \end{cases} \quad (2.6)$$

$$y_t = x_t \varphi_0^{(j)} + \sigma^{(j)} \varepsilon_t if, r_{j-1} < z_k < r_j \quad (2.7)$$

where $x_t = (1, y_{t-1}, y_{t-2}, y_{t-p}) j = (1, 2, \ldots, k)$ $and - \infty = r_0 < r_1, \ldots, r_n$.

**TAR Model with Two Threshold Variable:** The TAR model with two threshold variables which classifies observations $\boldsymbol{y_t}$ two regimes. Where

$$\begin{aligned} &\beta_o^{(i)} + \beta^{(1)} y_{t-1} + \beta_2^{(1)} y_{t-2} + \ldots + \beta_\rho^{(1)} y_{t-\rho 1} \\ &\quad + \upsilon_t, when, x_{1t} \leq \gamma_1^0, x_{2t} \leq \gamma_2^0 \end{aligned} \quad (2.8)$$

$\beta_0^{(2)} + \beta_1^{(2)} y_{t-1} + \beta_2^{(1)} y_{t-2} + \ \ldots \ + \beta_\rho^{(1)} y_{t-\rho 2} + \upsilon_t, when,$ $x_{1t} \leq \gamma_1^0, x_{2t} \leq \gamma_2^0$ Where $\left(\beta_0^1, \beta_1^j, \beta_2^j, \ldots, \beta_\rho^{(j)}\right)$ are coefficients, $\varepsilon_t^{\bullet} s$ are random error terms. The general LSTR model:

$$\begin{aligned} x_t = &\left(\alpha_0 + \sum_{i=1}^{p} \alpha_i x_{t-i}\right) + \left(\beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i}\right) \\ &+ G\left(s_{t-d}, \gamma, c + \varepsilon_t\right) \end{aligned} \quad (2.9)$$

where $G\left(s_{t-d},\gamma,c\right)$ is function, d is the decay, y is variable, c is threshold,$\alpha_0,\alpha_1,\alpha_2,...,\alpha_p$ and $\beta_0,\beta_1,\beta,...,\beta_p$ are the parameters and $\varepsilon_{t}$ $_=$error term.

$$y_t=\begin{cases}\mu_{1,0}+\rho_{1,1}y_{t-1}+\delta_1\varepsilon_t, if, y_{t-1}<\theta\\ \mu_{2,0}+\rho_{2,1}y_{t-1}+\delta_2\varepsilon_t, if, \theta<y_{t-1}\end{cases} \quad (2.10)$$

where $\rho_1$ is autoregressive, $\delta$ is noise SDs, $\theta$ is threshold and $\varepsilon_t$ is a zero 0 and 1variance [17] and TAR model [18] are popular nonlinear models.

Linearity Test SETAR Model: The null hypothesis of linearity can be expressed by the equivalence of the autoregressive parameters in the two regimes of the SETAR model [19].

Keenan Test (for SETAR): is nonlinearity analogous to Tukey's one degree of freedom for non-additively test [20].

#### The Jarque–Bera test

Breusch–Godfrey Lagrange Multiplier Test for Autocorrelation: Serial correlation is defined as correlation between the observations of residuals. The null hypothesis of the test is that there is no serial correlation in the residuals up to the specified order [21]. Estimation of the Order of the TAR: The lag length for the TAR (p) model may be determined using model selection criteria. The LSE of the threshold parameter the minimization of equality is the basic principle [22].

Model Validation Techniques: A large number of procedures are available for checking the adequacy of TAR. They used to indicate before a model is used for specific purpose to ensure that it represents the data adequately. Model Diagnostic Checks and Adequacy: is determining the adequacy or goodness of fit of a chosen model. The model diagnostic checks are performed on residuals and the standardized residuals [23]. Model Selection Criteria: The smallest information criteria were selected as a good model selection. Akaike Information criteria (AIC) by [24], Bayesian Information criterion (BIC) by [25] and Hannan–Quinn (HQ) by [26]. Forecasting: It was compared using performance measure indices. The accuracy of the models were compared using performance measure indices such as mean square error (MSE), mean absolute error (MAE) and mean absolute precision error (MAPE). A model with a minimum of MAE or RMSE was considered to be the best for forecasting [27].

## Results

#### Descriptive statistics for consumer price index (CPI)

The minimum inflation rate was 13.2; whereas, the maximum was 182.8 during the period from January 1994 and December 2020 with monthly data. The distribution test result was based on Jarque–Bera showed that the data appeared positively skewed and leptokurtic about their mean values revealing that inflation rate was more peaked from the mean value.

The average monthly inflation rate was obtained 53.28 with standard deviation of 45.98 during the study period. This shows that the standard deviation is very high indicating high level of fluctuations in the series. While, the kurtosis value was obtained for monthly inflation rate was 3.025 which exceeds 3, this means that the normal curve is peaked (leptokurtic). In addition, the dynamic structure of the inflation rates series contains an asymmetric pattern with a high variation among the observations and sample moments suggest that the right tail of the distribution is fatter than the left tail (Table 1).

#### Time series plot of the CPI

The plot indicates that the increasing pattern in inflation rate over time and this fluctuation of inflation rate could be also as a result of unstable market conditions. Yet again, inflation rate appeared stable from somewhere around the year 2011 to 2020 with interval of monthly data. A trend nature in the plot shows periodic pattern over time in regular intervals. Furthermore, both seasonal fluctuations and increasing trend which is an evident that both the mean and variance were changing over time. This implies that the monthly inflation rate was characterized by non-constant mean and an unstable variance (Figs. 1, 2, 3, 4).

#### Test of stationary of inflation rate

Stationary test result argument unit root test result showed that price index of inflation rate was not unit root or stationary at 5% level of significance. The series of different orders or lag2 and lag3 of consumer price index P value greater than level of significance level of 5% showing inflation a rate was unit rout or non-stationary for the unit root test, the null hypothesis of non-stationary was not rejected because the resulting P value was greater than 5% level of significance resulting none stationary which achieved after its stationary by differencing the series (Table 2).

**Table 1** Descriptive Statistics of CPI

| Mean | Median | Std | Min | Max | Skewness | Kurtosis | Jarque–Bera | Probability |
|---|---|---|---|---|---|---|---|---|
| 53.280 | 27.300 | 45.980 | 13.210 | 182.800 | 1.048 | 3.025 | 59.380 | < 0.001 |

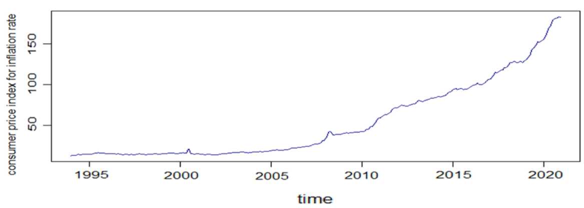


**Fig. 1** Time Series Plot of CPI (1994–2020)

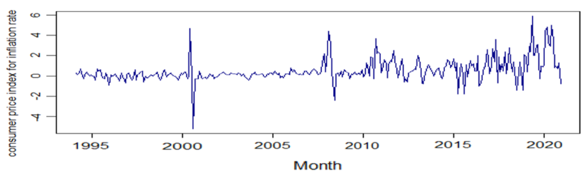


**Fig. 2** Time Series Plot of Differencing CPI

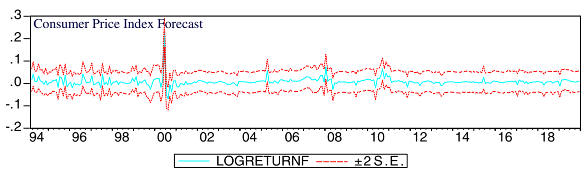


**Fig. 3** In-sample Forecast of Monthly CPI of Inflation Rate

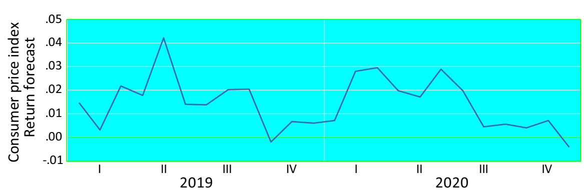


**Fig. 4** Out- Sample Forecast of Monthly Return CPI of Inflation Rate

### Chow break point test of CPI for inflation rate

To apply threshold autoregressive model (TAR) for time series data the linear (AR) model should be significant based on chow test. The performed test result of the chow test based on F-test statistic in Table 3 showed that there was structural break point in inflation rate. The structural break point that significant break date in the inflation rate exists, which is evident in (Appendix: Fig. 6) and the break date identified (Tables-4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, and 15).

### Econometrics modeling

ARIMA (1,1,1)(1,0,1)12, ARMA(1,1) and ARMA(2,1) models estimated parameters were significant since, their estimated P value were lower than 5% level of significance. The estimated intercepts for monthly rates of inflation for ARMA(1,1) was 0.276 with estimated

**Table 2** Unit Root Test CPI Monthly Inflation Rate

| Coefficient | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Intercept | −0.019 | 0.082 | −0.237 | 0.812 |
| Lag1-(Consumer price index) | 0.064 | 0.015 | 4.294 | < 0.001 |
| Lag2-(Consumer price index) | −0.065 | 0.060 | −1.083 | 0.275 |
| Lag3-(Consumer price index) | 0.102 | 0.575 | 1.775 | 0.076 |
| At difference | | | | |
| Intercept | 0.191 | 0.064 | 2.984 | 0.003 |
| Lag1-(Consumer price index) | −0.036 | 0.001 | −3.495 | < 0.001 |
| Lag2-(Consumer price index) | −0.233 | 0.071 | −3.119 | < 0.001 |
| Lag3-Consumer price index) | −0.084 | 0.056 | 1.775 | 0.134 |

**Table 3** Chow Test of CPI for Inflation Rate

| Testing type | Test Statistics | P value |
|---|---|---|
| F-Statistic | 640.2475 | < 0.001 |
| Log Likelihood Ratio | 354.2634 | < 0.001 |
| Wald Statistic | 640.2475 | < 0.001 |

**Table 4** Estimate Parameters of ARIMA Model for CPI

| Model | Variable | Estimate | Std.error | Z –Value | P value |
|---|---|---|---|---|---|
| ARIMA (1,1,1)(1,0,1)12 | AR(1) | 0.317 | 0.057 | 5.468 | < 0.001 |
| | MA(1) | −0.096 | 0.017 | −5.820 | < 0.001 |
| | SAR(1) | 0.125 | 0.058 | 2.141 | 0.0323 |
| | SMA(1) | 0.056 | 0.054 | −1.037 | 0.001 |
| ARMA (1,1) | Constant | 0.276 | 0.061 | 4.524 | < 0.001 |
| | AR(1) | 0.468 | 0.049 | 9.406 | < 0.001 |
| | MA(1) | −0.043 | 0.354 | 0.121 | < 0.001 |
| ARIMA(2,1) | Constant | −0.006 | 0.076 | −0.079 | 0.028 |
| | AR(2) | 0.807 | 0.049 | −16.469 | < 0.001 |
| | MA(1) | −0.491 | 0.049 | 1.002 | < 0.001 |

**Table 5** AIC and BIC for the ARIMA Models

| Model | AIC | BIC |
|---|---|---|
| AR(1,1) | 882.549 | 830.050 |
| AR(2,1) | 1111.995 | 1127.050 |
| ARIMA(1,1,1)(1,0 1)12 | 887.622 | 906.494 |

**Table 6** ARCH-LM test For The Squared Residuals of ARMA (1,1)

| Testing type | Test statistic | P value |
|---|---|---|
| F-test | 14.550 | < 0.001 |
| Obs*r-squared (LM Test) | 14.020 | < 0.001 |

**Table 7** Summary of the Linearity Tests Performed on CPI

| Likelihood Ratio Test | Test Statistic | P value | Order | Decision |
|---|---|---|---|---|
| No Threshold Linearity | 44.207 | < 0.001 | 11 | No threshold linearity, rejected |
| Threshold Nonlinearity | 35.140 | < 0.001 | 11 | Threshold nonlinearity, not rejected |

**Table 8** Tsay Test for Nonlinearity

| Order | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **F-test** | 0.37 | 0.470 | 3.000 | 1.870 | 2.260 | 2.80 | 2.680 | 2.250 | 1.860 | 2.020 | 2.490 | 2.480 |
| P value | 0.540 | 0.690 | < 0.001 | 0.04 | 0.04 | < 0.001 | < 0.001 | < 0.001 | 0.0007 | < 0.001 | < 0.001 | < 0.001 |

**Table 9** Estimates of Parameters for Lower and Higher Regime SETAR (2,2,3) for CPI

| Variables | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Intercept | 0.975 | 0.130 | 7.486 | 0.000 |
| Lag1-(CPI) | 1.073 | 0.088 | 12.169 | 0.000 |
| Lag2-(CPI) | −0.430 | 0.999 | −0.430 | 0.000 |
| Proportion (Low Regime) | | 29.690% | | |
| Intercept | 0.022 | 0.008 | 2.656 | 0.0085 |
| Lag1-(CPI) | 1.253 | 0.091 | −13.169 | 0.0311 |
| Lag2-(CPI) | −0.215 | 0.099 | −2.169 | 0.0311 |
| Lag-(CPI) | −0.041 | 0.0617 | −0.663 | 0.5075 |
| Proportion (High Regime) | | 70.310% | | |

**Table 10** Estimates of Parameters for Lower and Higher Regime SETAR(2,4,4) for CPI

| Variables | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Intercept | 0.522 | 0.136 | 3.827 | < 0.001 |
| lag1-(CPI) | 1.093 | 0.074 | 14.696 | < 0.001 |
| lag2-( CPI) | −0.861 | 0.106 | −8.051 | < 0.001 |
| lag3-(CPI) | 0.706 | 0.120 | 5.886 | < 0.001 |
| lag4-( CPI) | −0.128 | 0.068 | −1.880 | 0.063 |
| Proportion (Low Regime) | | 72.900% | | |
| Intercept-( CPI) | 0.019 | 0.218 | 2.252 | 0.0253 |
| Lag1-( CPI) | 1.330 | 0.071 | 18.639 | < 0.001 |
| Lag2-( CPI) | −0.351 | 0.118 | -2.968 | 0.003 |
| Lag3-( CPI) | 0.180 | 0.123 | 1.466 | 0.144 |
| Lag4-( CPI) | −0.162 | 0.078 | −2.072 | 0.039 |
| Proportion (High Regime) | | 27.100% | | |
| Threshold Value | | 174.300 | | |

**Table 11** Estimates of Parameters for Lower and Higher Regime SETAR(2,2,2) for CPI

| Coefficient | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Const. L | −0.415 | 1.484 | 0.279 | 0.779 |
| Lag1-(CPI) | −1.488 | 0.060 | 24.767 | < 0.001 |
| Lag2-( CPI) | −0.739 | 0.067 | −10.887 | < 0.001 |
| Proportion (Low Regime) | | 74.450% | | |
| Const. L | 0.687 | 0.637 | 1.079 | 0.281 |
| Lag1-( CPI) | −1.296 | 0.057 | 22.731 | < 0.001 |
| Lag2-( CPI) | −0.657 | 0.063 | 10.420 | < 0.001 |
| Proportion (High Regime) | | 25.550% | | |
| Threshold Value | | 6.600 | | |

**Table 12** Estimates of Parameters STAR CPI for Inflation Rate

| Coefficient | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Const | 0.258 | 0.062 | 4.127 | < 0.001 |
| Lag1-(CPI) | 0.436 | 0.056 | 7.783 | < 0.001 |
| Lag2-(CPI) | 0.068 | 0.056 | 1.223 | 0.2222 |

**Table 13** Estimates of Parameters LSTAR CPI for Inflation Rate

| Coefficient | Estimate | Std. Error | T-value | P value |
|---|---|---|---|---|
| Const. L | 0.254 | 0.062 | 4.071 | < 0.001 |
| Lag1-(CPI) | 0.390 | 0.065 | 5.968 | < 0.001 |
| Lag2-(CPI) | 0.0002 | 0.088 | 0.002 | 0.998 |
| Const. H | 1.593 | 0.499 | 3.193 | 0.001 |
| Lag1-(CPI) | 0.100 | 0.119 | 0.837 | 0.402 |
| Lag2-(CPI) | −0.406 | 0.183 | −2.215 | 0.026 |
| Gamma | 100.000 | 153.867 | 0.649 | 0.515 |

**Table 14** Model Comparison of CPI for the Inflation Rate Series

| Model | AIC | BIC | MAPE (%) |
|---|---|---|---|
| AR(1,1) | 882.549 | 830.050 | 231.2 |
| AR(2,1) | 1111.995 | 1127.050 | 240.4 |
| AR(1,1,1)(1,0,1)12 | 887.622 | 906.494 | 221.2 |
| SETAR(2,2,2) | −15.000 | −11.730 | 119.8 |
| SETAR(2,2,3) | −1470.000 | −1430.580 | 122.3 |
| SETAR(2,4,4) | −1500.000 | −1451.227 | 117.1 |
| STAR | −8.200 | −3.119 | 133.7 |
| LSTAR | −12.000 | −8.355 | 130.7 |

**Table 15** Normality Test for Standardized Residual from SETAR (2,4,4)

| | Statistic | T test | P values |
|---|---|---|---|
| Skewness | 2.505 | 2.2300 | 0.001 |
| Excess Kurtosis | 20.849 | 4967.300 | < 0.001 |
| Jarque–Bera | 3214.250 | – | < 0.001 |

standard error of the monthly rates of inflation was 0.06 shows that inflation rate within a particular month can change as the standard error was less than 1. Generally, the significances of the estimated parameters implied that there was strong relationship the monthly rates of inflation its lag value.

To select an appropriate one among the estimated candidate models their AIC and BIC values were compared and the model having minimum value was considered as the good model. As described [28], the selected model is not necessary provides best forecasting results. Therefore, the main interest in the model that has been given the best out of sample forecast results. From the estimated candidate models, using the method maximum likelihood the estimated parameters of the models of ARMA(1,1) was the best with the minimum AIC and BIC conditional mean equation.

### Test for ARCH effects

The test for the ARCH LM effects for the residuals of ARMA(1,1) model was done and the result presented in Table 15. This result revealed that the rejection of no ARCH effect in residuals from the mean equation for the series of the consumer price index. This test result was the confirmation for the presence of ARCH effect which indicates that the inflation rate is time varying and appropriateness of estimating TAR family model.

### Nonlinearity test for CPI

P value = 0.000416 which is statistically significant. The null hypothesis is rejected with conclusion that monthly inflation rates were a nonlinear process. In the likelihood ratio test for threshold nonlinearity: The null hypothesis assumes that the time series follows an AR($p$) model. While, the alternative hypothesis specifies that the time series follows a two-regime threshold autoregressive (TAR) showed the rejection of the null hypothesis for no threshold linearity. The P value is less the 5% significant level and concluded that the inflation rates were nonlinear.

### Tsay test for CPI

From Table 16 revealed that P values of Tsay test implies that there is no enough evidence to reject the null hypothesis of no nonlinear threshold in autoregressive order one and two. Whereas the AR(3), AR(4), AR(5), AR(6) and AR(12) have nonlinear thresholds. The empirical studies on financial time series revealed that the Inflation rate was nonlinear. Tsay tests for lags 3 to 12 rejected the null hypothesis of linearity. This was also true for larger number of lags. These results promote us to carry on our investigation using nonlinear features of the time series for inflation rate. SETAR model is preferable to model the inflation rate with order (3–12) than simple AR.

### Parameter estimation and evaluation for nonlinear model

An average of 0.975 for the monthly rates of inflation to switch from a lower regime. The standard error of the monthly rates of inflation was 0.130 and 0.008 for low and high regimes, respectively. This implied that the coefficient of consumer price index required for inflation rate to decrease lower regime to higher regime. This shows that inflation rate can change within a particular month. As the standard errors for coefficient of inflation for lower regime was less than 1. The standard errors from the result are relatively high in the low regime as compared to the low standard error in the high regime. The t-statistic value for the lower regime was 7.486 and that of high regime was 2.656. These values were far from zero which is an indication of strong relationship in the monthly rates of inflation.

All estimators in lower regime and most of estimators in upper regime are significant. From the Model output, the p values for both regimes were less than 5% of the significant value shown consumer price index of inflation and lagged vale of inflation more related. The proportion

**Table 16** Lagrange Multiplier ARCH Test for SETAR (2, 4, 4) model

| Order | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| ARCH-LM Test | 257.5 | 121.4 | 71.7 | 49.3 |
| P value | < 0.001 | < 0.001 | < 0.001 | < 0.001 |

points in low regime of 29.69% and high regime of 70.31%, respectively. This implies that more investors were leaving the market in the high regime as a result of fewer opportunities available on the market. This signified that the investor's positive changes any time the inflation index is below or above 0.1. The two regimes have different slop, a sign of statistically significant threshold effect. The results from the estimated lower regime also decreasing phase while the higher regime corresponds to the increasing phase. The coefficient in the higher regime indicates decreasing profit for investors.

The fitted residuals were 0.522 for the monthly rates of inflation to switch from a lower regime. The standard error of the monthly rates of inflation was 0.136 and 0.008 for low and high regimes, respectively. This implied that the coefficient of consumer price index required for inflation rate to decrease lower regime to higher regime. This shown that inflation rate can change within a particular month. The standard errors for coefficient of inflation for lower regime and higher were less than 1. The standard errors from the result are relatively low in the low regime as compared to the high standard error in the high regime. All most estimators in upper regime and all most of estimators in lower regime are significant. The two regimes have different slop, a sign of statistically significant threshold effect. The P values for both regimes were less than 5% of the significant value shown consumer price index of inflation and lagged vale of inflation more related.

The proportion points in low regime of 72.900% and high regime of 27.100%, the results from the estimated lower regime also an increasing phase while the higher regime corresponds to the decreasing phase. When the inflation rate is low, investors take an advantage of entering into the market in order to secure high profit. There was also an inflation rate decrease in the upper regime or High regime: 27.100% while the remaining number in the lower regime 72.9% was greater than higher regime. This implies that more investors were leaving the market in the lower regime as a result of fewer opportunities available on the market. This signified that the investors' positive changes any time the inflation index is below or above 174.3. The coefficient in the higher regime indicates increasing profit for investors.

A coefficient was -0.415 for the monthly rates of inflation to switch from a lower regime to a higher regime. The standard error of the monthly rates of inflation was 1.484 and 0.637 for low and high regimes. The coefficient of consumer price index required for standard error of the inflation rate was 1.484 for lower regime and 0.637 for higher regime. This shown that inflation rate can change within a particular month as the standard errors for coefficient of inflation for lower regime were greater than 1.

The standard errors from the result are relatively high in the low regime as compared to the low standard error in the high regime. All most estimators in upper regime and all most of estimators in lower regime are significant. The P values for both regimes were less than 5% of the significant value showing consumer price index of inflation and lagged vale of inflation more related. the proportion points in low regime of 74.450% and high regime of 25.550%. The results from the estimated lower regime also decreasing phase while the higher regime corresponds to the increasing phase.

The inflation rate is low; investors take an advantage of entering into the market in order to secure high profit. 25.550% while the remaining number in the lower regime 74.450% was greater than higher regime. This implies that more investors were leaving the market in the lower regime as a result of fewer opportunities available on the market. This signified that the investors' positive changes any time the inflation index is below or above 6.600. The coefficient in the higher regime indicates increasing profit for investors (Appendix: Fig. 5).

### Smooth threshold autoregressive model (STAR) for CPI

Both lag1-CPI and lag2-CPI are the lower order coefficients for lower regime, the constant for the lower regime. An average coefficient of 0.258 for the monthly rates of inflation to switch a smooth transition the standard error of the monthly rates of inflation was 0.062. This shown that inflation rate can change within a particular month as the standard errors was less than one. The t-statistic value for the smooth transition regime was 4.127. P values for smooth transition of coefficient were less than 5% of the significant value. The smaller the value of probability value, the more significant CPI of inflation and lagged value CPI of inflation are more related.

### Logistic smooth threshold autoregressive (LSTAR) models

There were a significant number of observations in the upper regime for constant value was 1.593 while, the remaining number in the lower regime was 0.254. The coefficient in the higher regime indicates that an increasing inflation rate than lower regime. The switching regime indicates that the investors were attracted by high profit and unwilling to bear higher risks coefficient of CPI required for standard error of the inflation rate were 0.062 for lower regime and 0.499 for higher regime. This show that inflation rate can change within a particular month as the standard errors for coefficient of inflation for lower regime were less than 1. The standard errors from the result are relatively low in the low regime as compared to the high standard error in the high regime. The t-statistic value for coefficient the lower regime was 4.071 and that of high regime was 3.193 these values were far from zero which is an indication of strong relationship monthly rates of inflation.

#### Jarque–Bera test for CPI

The normality test result based on computed Jarque–Bera Test statistic value of 5.380 ($P=0.063$) showed that data are normally distributed. Generally, the null hypothesis is rejected for smaller P values less than 5% level of significance. Hence, the data under consideration are said to be normally distributed ($P=0.063>0.05$). In this case, we would fail to reject the null hypothesis that the data are normally distributed.

#### Breusch–Godfrey Lagrange multiplier test for autocorrelation

Durbin–Watson test value of 1.0625 ($P=0.052$) revealed that autocorrelation not exists among the residuals. The model free from any serial correlation because the computed P value for the test is greater than level of significance. The corresponding P value is greater than 0.05 level of significance, we do not reject the null hypothesis and SETAR(2;4,4) model were free from serial correlation or autocorrelation.

#### Model comparison for the inflation rates of time series

In this study, a SETAR(2,4,4) model has the minimum AIC and BIC values of -1500 and -1451.227 was considered as an appropriate one. Therefore the most adequate model is specified by accuracy measured. In terms of AIC criteria with SETAR having advantage over linear and nonlinear time series model.

#### *Diagnostic checks and adequacy SETAR(2,4,4) models*

The residuals exhibit random variation about their mean and hence it can be concluded that the residuals appear to be random. However, the histogram plot of standardized residuals the SETAR(2,4,4) model it can be observed that the residuals are approximately not normal though there are few extreme values in the tails.

#### *Normality test for residual from SETAR(2,4,4)*

The result shows that the normality of the residuals in the fitted model was rejected. Therefore, we conclude that the residuals of the fitted model were not normally distributed (Appendix: Fig. 8).

This test results leads to reject the null hypothesis of no ARCH effects since the test statistic was in order 4 was 49.3 with a probability value of 1.55e-05, which is less than 5% significance level and this test result implied that SETAR(2,4,4) model provides an adequate representation of the data since most of the model adequacy conditions were satisfied (Appendix: Fig. 7).

#### *Forecasting models*

### In-sample forecasting using SETAR(2,4,4) model

From CPI of inflation rate steadily increased from the years 1994 to around 2000 and from the year 2001 to year 2019 shows that almost similar level. Moreover, low inflation rate was observed around the end of the study periods (Fig. 3).

### Out-sample forecasting using SETAR(2,4,4) model

The plot indicates that the forecasting of inflation rate was used for in-sample estimate from January 2019 to December 2020 (Fig. 4).

### Forecasting evaluation and accuracy criteria

The forecast measure MAE and MSE suggest that the nonlinear SETAR model outperform the linear ARMA model. This nonlinear model also produced minimum forecast errors as compare to linear ARIMA model. The SETA(2,4,4) model was performed the least in forecasting the conditional volatility of the monthly rates of inflation.

### Forecast output of one year monthly rates of inflation (May 2020 to April 2021)

There is low amount of variation in the monthly rates of inflation and this might pose great challenges to other economic variables. Although, the nonlinear model is superior in forecasting the monthly rates of inflation. The superiority in performance of nonlinear model was attributed to their ability to capture the stochastic nature of the monthly rates as is evident in the pattern of the forecast errors (Tables 17, 18).

## Discussion

This study was investigated to develop modeling and forecasting the inflation rate in Ethiopia over the study periods from January 1994 to December 2020 in monthly data interval. To fit SETAR model for the inflation rate the nonlinear test was performed using the Keenan and Tsay tests and the resulting P values of the test statistics were less

**Table 17** Forecast Comparison of Accuracy Models

| Model | MAE | MSE | MASE |
|---|---|---|---|
| AR(1,1) | 0.621 | 0.980 | 0.761 |
| SETAR(2,4,4) | 0.615 | 0.877 | 0.885 |
| LSTAR(2,2,3) | 0.993 | 0.894 | 0.776 |

**Table 18** Forecast Output for One Year with Monthly Rate of Inflation

| Month | May-20 | Jun-20 | July-20 | Aug-20 | Sep-20 | Oct-20 | Nov-20 | Dec-20 | Jun-20 | Feb-20 | Mar-20 | Apr-20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SETAR(2,4,4) | 1.06920 | 1.0675 | 1.0657 | 1.0662 | 1.0666 | 1.066478 | 1.066420 | 1.066454 | 1.066463 | 1.066455 | 1.066454 | 1.066455 |

than 5%, implying the datasets follow threshold nonlinear series. The behavior of inflation rate of India, Pakistan and Sri Lanka using the TAR model proposed by [29].

In the presence study, ARMA(1,1) and SETAR (2,4,4) are best models from the empirical results of AIC and or BIC value in predicting inflation rates. This finding result was also confirmed with the [30] using a nonlinear quadratic model empirically, estimated the threshold level of inflation for Kenya, Tanzania and Uganda for the period 1970 to 2013. This assessment result found that superiority in performance of SETAR(2,4,4) models is to measure forecast accuracy attributed to their ability to the monthly rates of inflation. This finding result was also confirmed with the study of Taiwan inflation rate [31] that found the SETAR model to better examine the out of sample forecast of than other linear and nonlinear time series.

The P values for both regimes were less than 5% of the significant value shown consumer price index of inflation and lagged vale of inflation more related. The proportion points in low regime of 72.900% and high regime of 27.100%. The results from the estimated lower regime also an increasing phase while the higher regime corresponds to the decreasing phase. When the inflation rate is low, investors take an advantage of entering into the market in order to secure high profit. There were also inflation rate in the upper regime or High regime: 27.100% while the remaining number in the lower regime 72.9% were greater than higher regime. This implies that more investors were leaving the market in the lower regime as a result of fewer opportunities available on the market. This signified that the investors' positive changes any time the inflation index is below or above 174.3. The coefficient in the higher regime indicates increasing profit for investors.

## Conclusion

The core objective of this study was intended to modeling inflation rate factors on present consumption price index (CPI) in Ethiopia: using the application of threshold autoregressive (TAR) models. There were inflation rate decreases in the upper regime was 27.100% and lower regime was 72.9%, which was greater than higher regime. The SETA(2,4,4) model performed the least in forecasting the conditional volatility of the monthly rates of inflation in Ethiopia.

The superiority in performance of nonlinear models was attributed to their ability to capture the stochastic nature of the monthly rates as evident in the pattern of the forecast errors. The investigators are recommended that using TAR models policy makers can be able to capture the price volatility persistence and also forecasting can be made.

## Limitations of the study

This study has been limited to secondary data source on macroeconomic variable was obtained from CSA during the period from January 1994 to December 2020 in monthly data. These data were collected simple for the purpose of monitor changes in price movements and to observe its effect on their program implementation and policy decision. The future investigator will be better to take in account a primary source and key variables under the study, to reduce the inflation rate in Ethiopia.

## Appendix

See Figs. 5, 6, 7 and 8.

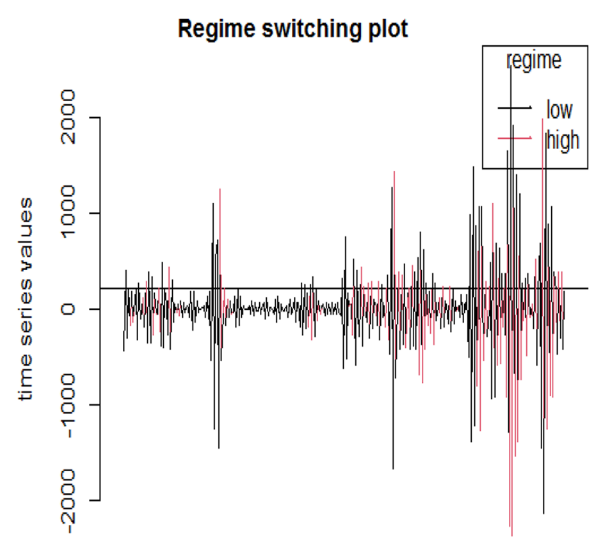


**Fig. 5** Regime Switching Plot for CPI SETAR(2,2,2)

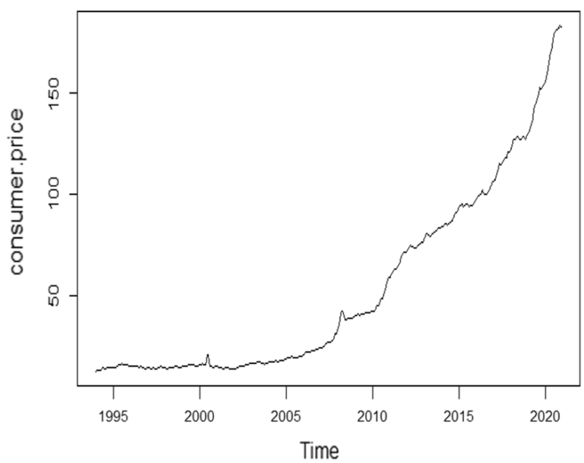


**Fig. 6** Structural Change Break Point on CPI for IR

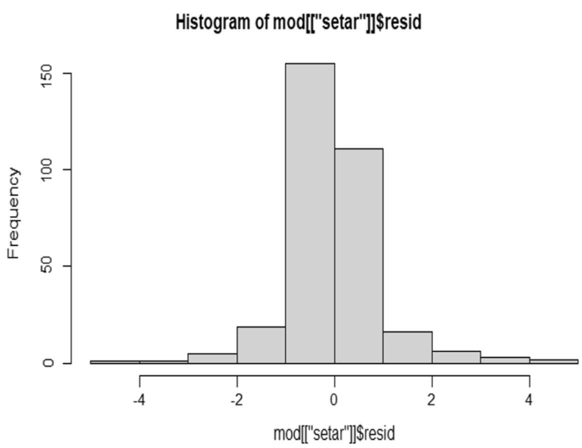


**Fig. 7** Histogram Plot of Standardized Residuals the SETAR(2,4,4) Model

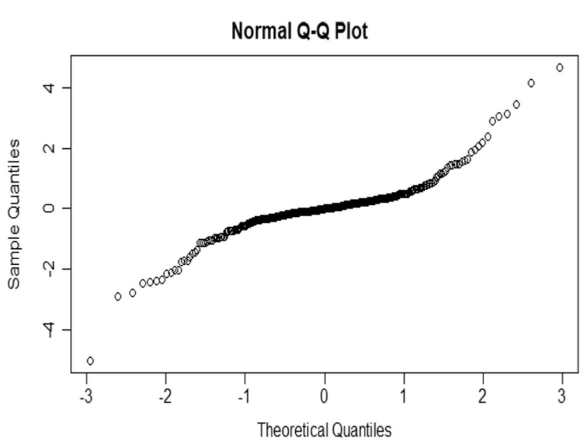


**Fig. 8** Normal Probability Plot of Residuals SETAR(2,4,4)

**Abbreviations**

| | |
|---|---|
| ACF | Autocorrelation function |
| ADF | Augmented dickey–fuller test |
| AIC | Akakie information criteria |
| AR | Autoregressive |
| ARIMA | Autoregressive integrate moving average |
| ANN | Artificial neural network |
| CPI | Consumer price index |
| CSA | Central statistical agency |
| EWMA | Exponential weighted moving average |
| EGACH | Exponential generalized autoregressive conditional heteroscedastic |
| FIES | Family income and expenditure survey |
| GARCH | Generalized autoregressive conditional heterokedast |
| GDP | Gross domestic product |
| BIC | Bayesian information criteria |
| HQIC | Hannan–Quinn information criteria |
| IMF | International monetary fund |
| LM | Lagrange multiplier |
| SD | Standard deviation |
| LSTARM | Logistic smooth threshold autoregressive model |
| MOFED | Ministry of finance and economic development |
| MAP | Mean absolute percentage |
| MSE | Mean square error |
| NAIRU | Non-accelerating inflation rate of unemployment |
| NBE | National bank of Ethiopia |
| PACF | Partial autocorrelation coefficient |

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**Author contributions**
BK developed the original draft preparation, validation and conceptualization; AT data collection and data management; and AA data analysis, interpretation and report writing.

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**Availability of data and materials**
This work is basically considered the manufacturing firms reside in Central Statistical Agency. But, the required data will be provided about the inflation rate and consumption prince index were considered under this study.

## Declarations

**Ethical approval and consent to participate**
Ethical clearance had been obtained from Department of Statistics, Haramaya University, Ethiopia.

**Consent for publication**
This manuscript has not been published elsewhere and is not under consideration by another journal. Authors had approved the final manuscript and agreed with its submission to this journal. We agreed about authorship for this manuscript.

**Informed consent**
Not applicable!

**Competing Interests**
The authors declare that no competing interests.

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## Publisher's Note



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