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Forecasting Inflation Rate of Bangladesh Using Exponential Smoothing (ETS)

Rushad Faridi[1]
Md. Saiful Islam[2]

A R T I C L E I N F O

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A B S T R A C T

The focus of the study is forecasting performance of Exponential Smoothing (ETS) models for Bangladesh's inflation rate. We have used officially published monthly data covering 2000-2024. Inflation in Bangladesh has not followed a smooth or stable path over this period, with episodes of food price spikes, exchange-rate pressures, and policy shifts, which makes forecasting particularly challenging. Instead of imposing a single specification, we estimate and compare a range of ETS models, since different structures capture trend, seasonality, and short-run movements in different ways. Based on out-of-sample forecast accuracy, one ETS specification consistently performs better than the others. When its forecasts are compared with those from standard ARIMA models, ETS appears to track turning points and short-term movements more closely, although the differences are not uniform across all horizons. These results suggest that ETS provides a useful and relatively flexible framework for forecasting inflation in Bangladesh, and may be especially well suited to emerging economies where inflation dynamics tend to shift over time.

1. Introduction

Inflation is widely regarded as one of the major economic challenges, particularly in developing nations (Omekara et al, 2013). Since its independence, the

[1]Assistant Professor, Department of Economics, University of Dhaka, Dhaka, Bangladesh. Email: faridir@gmail.com
[2] Assistant Professor, Department of Economics, University of Dhaka, Dhaka, Bangladesh. Email: saifulecon@du.ac.bd

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Bangladeshi government has faced repeatedly the ongoing macroeconomic challenge of maintaining price stability (Siddiquee & Faruk, 2020; Salma, 2021; Ahmed, 2023). More recently, Bangladesh has been grappling with the issue of inflation since the onset of the Ukrain-Russia war (Kilfoyle, 2023). Since the outbreak of the Ukraine–Russia war, inflation control has moved to the center of policy debates across many countries, and Bangladesh has not been any different. Price stability has become a daily concern not just for policymakers but also for households and businesses. At the same time, several domestic policy choices appear to have added to inflationary pressures rather than easing them (Khatun, 2023), which has only increased uncertainty about where prices are heading. As a result, interest in the likely future path of inflation has grown sharply among government agencies, market participants, and the general public.

During the 2022–23 fiscal year, average inflation in Bangladesh climbed to around 9 percent, well above the roughly 6 percent that had prevailed in earlier years. Food prices have been doing much of the damage. For most of fiscal year 2023–24 prices were running above 10 percent, and that alone explains a large share of the headline inflation rate. BBS (2024) reports that this has recently moved past 12 percent for three months in a row. When food prices behave this way, forecasting inflation stops being a purely technical exercise and turns into a practical necessity for anyone trying to design policy or even plan a household budget.

In time-series analysis, forecasting a single variable like inflation may involve a choice between two primary methods: Exponential Smoothing (ETS) and the Box-Jenkins (ARIMA) approach (Wan, Ahmad & Ahmad, 2013). While ETS can be applied to many economic indicators, we focus here on its application in analysis of inflation rate. We selected ETS for this study not for variety, but for practicality. Traditional ARIMA method usually require rigorous statistical tuning and expert model selection. On the other hand, ETS, most of the time, offer distinct advantages in speed and ease of implementation. Moe often than not, it is capable of producing It reliable short-term forecasts without the heavy computational demands that often complicate ARIMA modeling. Exponential smoothing is widely used globally to forecast inflation, yet it's application in the specific context of Bangladesh was limited. Researchers have extensively studied the relationship between inflation and other macroeconomic variables, developed univariate models using ARIMA, but we did not find any application of ETS methods in forecasting inflation rate or any other macroeconomic variable. This paper aims to close that gap. By testing ETS against established methods, we make an effort to provide a modeling framework tailored to the local needs of Bangladesh. By testing ETS directly against established methods, we hope to provide a modeling framework that actually serves the local needs of Bangladesh. Consequently, it may present an opportunity to develop more effective forecasting models to predict inflation rate of Bangladesh.

With this background, aim and objectives, the remainder of the paper is structured as follows: Section 2 offers an overview of current exponential smoothing methods.

In Section 3, we describe the data used in this study, focusing on the inflation rates of Bangladesh, including their source and general trends. Section 4 introduces various models and identifies the most suitable one based on different model selection criteria. Section 5 generates forecasts using these models while Section 6 presents the discussion and concluding remarks.

2. Literature Review

Exponential smoothing, introduced in the late 1950s by Brown (1959), Holt (2004) and Winters (1960), has served as the inspiration for many highly effective forecasting techniques. It involves generating forecasts through weighted averages of historical data points, with the weights diminishing exponentially as the data ages. Essentially, more recent data points carry greater significance in this method. This approach facilitates the rapid generation of dependable forecasts across various types of time series data, offering a significant advantage for industrial applications.

There have been lots of use of this exponential technique. The inflation rate of Ghana has been modeled using various exponential smoothing techniques, considered as the most suitable approach (Ofori & Ephraim, 2012). Jere & Siyanga (2016) used this method in the case of Zambia's inflation data. Another study by Lidiema (2017) used a mixture of SARIMA and exponential smoothing in inflation forecasting for Kenyan economy. A related study using United States' inflation data, employed multitude of models including ARIMA, Neural Network and exponential smoothing (He et al. (2012)). According to Okereke & Bernard (2014), the SARIMA (2,1,2) model provided the best fit for the GDP data of the Nigeria based on the Schwartz Information Criterion (SIC) and adjusted R-squared. Extensive work has also been done on time series modeling of inflation rate in Bangladesh but none involved exponential smoothing technique. Quite a few studies exist on investigating determinants of inflation (Uddin et al. (2014). Relationship between inflation and economic growth has also been extensively explored by A. A. Hossain (2015). Additionally, there are research works which investigated relationship between inflation and other macroeconomic variables in Bangladesh. For instance, studies have explored the connection between remittances and inflation (Khan & Islam, 2013), impact of inflation on exchange rate (Mostafa, 2020), effect of inflation on income inequality (Muhibbullah & Das, 2019) etc. In one such research endeavor, Rahman et al. (2020) went through the exercise of modeling inflation rate through ARIMA framework. Akhter (2013), Islam (2017) and Faisal (2012)'s study is in similar scope while the former incorporated seasonality in the model.

The overview provided indicates that there has been a notable lack of significant research on inflation forecasting for Bangladesh utilizing the exponential smoothing technique. This research aims to address this gap by applying the exponential smoothing technique to inflation forecasting for Bangladesh. We already have noted in our introductory section that exponential smoothing has certain advantages over other time series techniques for forecasting. In the next section we discuss ETS methods in greater detail followed up a brief description of the advantages of this method.

Different ETS methods

2.1 Simple Exponential Smoothing (SES)

Simple exponential smoothing (SES) is the simplest form of exponential smoothing. When the data has no clear seasonal pattern or trend, this method becomes useful. There are different representation of SES models. In the component form, these models can be formulated in the following two equations (Hyndman et al., 2008) :

Forecast equation: $\hat{y}_{t+h\vee t} = l_t$

Smoothing/level equation: $l_t = \alpha y_t + (1-\alpha)l_{t-1}$

In the forecasting equation, h represents the future time period forecast which is equivalent to the level of the series. In smoothing equation, l_t represents the level or the smoothed value of the series at time t and α is the smoothing parameter for the level where $0 \leq \alpha \leq 1$. As we have mentioned above, when the data have trend or seasonal pattern, this method might not be that useful. But it sets the foundational ground for other more complicated scenario discussed below.

2.2 Models with linear trend

In these models, simple exponential smoothing is extended to include trend component first proposed by (Holt, 2004). In this method forecast equation is combined with two smoothing equations (one for the level and one for the trend) (Makridakis et al., 1998) :

Forecast equation $\hat{y}_{t+h\vee t} = l_t + hb_t$

Level equation $l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend equation $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$

Here the additional term added from the previous SES model includes b_t

which provides an estimate of the trend (slope) of the series at time t. We also have β which is the smoothing parameter for the trend where the values are restricted to $0 \leq \beta \leq 1$.

2.3 Damped trend methods

The limitation of Holt's linear trend method is that it displays a constant trend indefinitely in the future. This is unlikely to happen since we expect the distant future may have reduced impact on the trend. This reduced or "dampening" impact is absent in Holt's method. To improve upon Holt's methodology, Gardner Jr & McKenzie (1985) proposed a parameter that will perform this "dampening" effect and the forecasts in the distant future will reduce to a flat line. In addition to parameters α and β in Holt's method, there is also a dampening parameter with this additional parameter, this damped trend methods have the following form:

Forecast equation: $\hat{y}_{t+h \vee t} = l_t + (\phi + \phi^2 + \cdots + \phi^h)b_t$

Level equation: $l_t = \alpha y_t + (1-\alpha)(l_{t-1} + \phi b_{t-1})$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)\phi b_{t-1}$

In the above model, when $\phi = 1$, it boils down to Holt's linear method. When the values of ϕ such that $0 \leq \phi \leq 1$, the dampening of trend is in effect and as a result the forecasts becomes flat as time periods move far into the future.

2.4 Models with seasonality

Holt's (1957) method was enhanced by Holt and Winters (1960) to incorporate seasonality. In this formulation, there are four equations in total: one forecast equation and three smoothing equations. These models have two variations, one with additive seasonality when the seasonal pattern is roughly constant throughout the observed period of the data. Multiplicative model is applied when seasonal variations changes in proportion to the level of the series. In the following we describe the analytical structure of the both of these forms:

Seasonal additive models

Compared to trend models mentioned above, there is additional one equation which incorporates additive seasonal pattern and denoted by s_t:

Forecast equation: $\hat{y}_{t+h \vee t} = l_t + hb_t + s_{t+h-m(k+1)}$

Level equation: $l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$

Seasonal equation: $s_t = \gamma\gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma\gamma)s_{t-m}$

We have to note few changes from the trend model we have seen above. First of all, it is required that estimates of the seasonal indices used in forecasting is available at the end of the period. k which is the integer portion of $\frac{(h-1)}{m}$ ensures this requirement is fulfilled (Petropoulos et al., 2014). Then, the level is formed with a weighted average of seasonally adjusted observations $(y_t - s_{t-m})$ and the non-seasonal forecast $(l_{t-1} + b_{t-1})$ for time t. The trend equation does not differ from Holt's linear method. Lastly, a weighted average between the current seasonal index $(y_t - l_{t-1} - b_{t-1})$ and the seasonal index of the same season last year (m) forms the seasonal equation.

Seasonal multiplicative models

Multiplicative models incorporating seasonality is an extension of the damped trend models with the following form:

Forecast equation: $\hat{y}_{t+h \vee t} = (l_t + hb_t)s_{t+h-m(k+1)}$

Level equation: $l_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$

Seasonal equation: $s_t = \gamma\gamma \frac{y_t}{(l_{t-1}+b_{t-1})} + (1-\gamma\gamma)s_{t-m}$

We note here how the seasonal component is changed compared to additive model to incorporate the multiplicative nature of seasonality.

Seasonality with damped method

Previously, we have argued that trend models with dampening parameter provides more realistic and accurate forecasts. We can do the same in the case of seasonal models which will enhance the forecasting accuracy. Therefore, our final model is in the following form:

Forecast equation: $\hat{y}_{t+h \vee t} = [l_t + (\phi + \phi^2 + \cdots + \phi^h)b_t)s_{t+h-m(k+1)}$

Level equation: $l_t = \alpha(y_t/s_{t-m}) + (1-\alpha)(l_{t-1} + \phi b_{t-1})$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)\phi b_{t-1}$

Seasonal equation: $s_t = \gamma\gamma \frac{y_t}{(l_{t-1}+\phi b_{t-1})} + (1-\gamma\gamma)s_{t-m}$

As we have already seen in the damped trend models, ϕ acts as the dampening parameter which affects all four components of above formulation.

In this section, we provided a brief overview of various ETS methods. Now, we will proceed to introduce the inflation data that will serve as the basis for estimating a suitable forecasting model among those discussed in this section.

2.5 Advantages of ETS methods

Exponential Smoothing has several advantages over ARIMA, particularly in certain scenarios. These advantages typically relate to simplicity, ease of implementation, and practical application in time series forecasting.

Exponential Smoothing models, especially the basic forms (like Simple Exponential Smoothing or Holt-Winters), are relatively easy to understand, configure, and implement. These methods usually do not require as much deep statistical expertise or parameter tuning as ARIMA models do. ETS methods also may require fewer parameters to estimate, making it easier and faster to fit models. For example, Simple Exponential Smoothing may require an estimation of only a smoothing parameter, while ARIMA typically require determining AR, I, and MA terms, which can be complex. Exponential Smoothing models are also usually faster to compute compared to ARIMA models, especially when dealing with large datasets or needing quick updates to forecasts. For this reason, many researchers consider Exponential Smoothing particularly suitable for real-time forecasting where computational resources are limited or when quick turnaround times are necessary.

Another attractive feature of ETS models is these models place more weight on recent observations. As a result, they can capture changes in trends and patterns more quickly for short-term projections. Exponential Smoothing (especially Holt-Winters method) allows for explicit modeling of trends and seasonality in time series data. This is done without requiring the data to be stationary, which is a requirement for ARIMA. In contrast, ARIMA handles trends and seasonality through differencing and seasonal ARIMA (SARIMA), which can be more complicated. Exponential Smoothing methods, especially Holt's and Holt-Winters, can effectively model non-stationary data with a trend and/or seasonality. This makes it most of the time easier to use on raw time series data without having to worry as much about making the series stationary through differencing or other transformations, as required by ARIMA. Since Exponential Smoothing gives more weight to recent data, it might be able to smooth out noise better in some cases compared to ARIMA, which tries to model the underlying structure of the series, including noise components. As a result, time series modelers may find ETS as a faster, more straightforward choice, especially for users who are not familiar with time series modeling nuances.

3. Data description

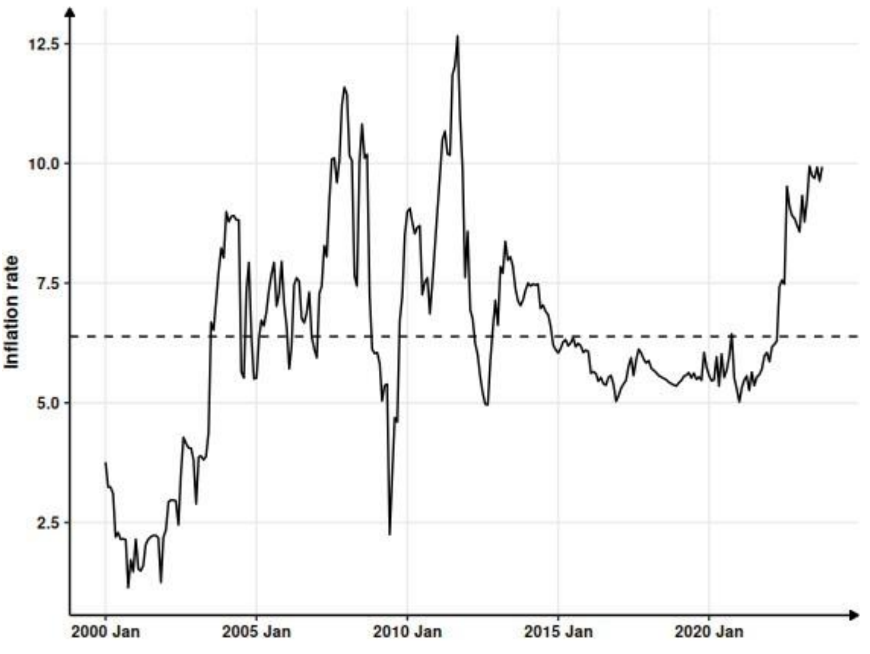
Data has been gathered from various editions of economic trends (Bangladesh Bank, 2000-2023). Monthly economic trend data has been available for many decades, with Bangladesh Bank (2000-2023) being the main source. However, the primary data collection is conducted by the Bangladesh Bureau of Statistics (BBS). Each month, the BBS publishes Consumer Price Index (CPI) data along with corresponding inflation figures (BBS, 2024).

The BBS gathers price data from 154 main markets across the country, comprising 90 urban markets (including 12 from Dhaka City, 04 from Chattogram City, 18 from Other 06 Divisional Cities, and 56 from other Districts) and 64 rural markets in 64 Districts (Bangladesh Bureau of Statistics, 2021). In each market, three price quotations per item, along with their varieties, are collected. Both rural and urban areas are surveyed monthly, while Dhaka and Chattogram City Corporation areas are surveyed weekly each month. Prices are typically collected from selected shops in each market or selected service providers for services. In constructing price indices, the average price for each item is considered.

For the computation of CPIs, two consumer baskets are employed: the urban basket and the rural basket. These baskets include goods and services determined based on the Household Income and Expenditure Survey (HIES) of 2016-17 for private consumption (Bangladesh Bureau of Statistics, 2019). Both urban and rural baskets encompass 383 items with 749 varieties of food and non-food items (goods and services). The item weights in the base year are determined based on the average expenditure incurred by a household on the item, expressed as a percentage share of the total expenditure on all items (Bangladesh Bureau of Statistics, 2020).

In Figure 1 we find the inflation in the last two decades of Bangladesh. We find that in early 2000 the inflation was quite below the historic average of 6.30. After 2008, we start to experience some wild fluctuations in the inflation data and this pattern continued till 2014. Later it achieved some stability up to 2021. Since the Ukrain- Russia conflict, not surprisingly, the price started to creep up again. It signals there might be some volatility in inflationary pattern ahead.

Figure 1: Overall inflation pattern



Source: Various editions of Economic Trends (Bangladesh Bank)

4. Selection of optimal ETS model

In this section, we are going to estimate the models we have discussed in Section 2 with the data described in the previous section. Our main objective is to select the optimal model from these multitude of ETS models. Before we begin this endeavor, we present a brief description the model selection measures that will be used to find the optimal ETS method.

The most elementary measure for model selection is R^2. But it is not a good measure of predictive ability of a model since it depends on the numbers of regressors added to the model (Montgomery et al., 2012). Adjusted R^2 corrects this problem but it still errs on too many predictors (Myers, 2012). To improve upon these concepts, a related method is introduced namingly Akaike's Information Criterion (Akaike, 1974) , which is defined as :

$$\text{AIC} = Tlog\,(\frac{\text{SSE}}{T}) + 2(k+2)$$

Here T is number of the observations, SSE is sum of squared errors and k is number of predictors. $k + 2$ indicates that there are $k + 2$ number of parameters that need to be estimated with k number of coefficients for each predictor and the rest 2 for intercept and variance of the residuals. The best model is the one which minimises AIC. With the penalty term $2(k + 2)$, AIC penalizes any model for having more predictors than other models.

If the number of observations (T) is smaller, the AIC tends to select models with too many predictors. To correct this bias, an alternative version of AIC is proposed (Hurvich & Tsai, 1989) which is shown below:

$$\text{AIC}_\text{c} = \text{AIC} + \frac{2(k+2)(k+3)}{T-k-3}$$

As in the case of AIC, we also need to minimize AIC_c in order to find the optimal model.

Another related measure is Schwarz's Bayesian Information Criterion (BIC) (Schwarz, 1978):

$$\text{BIC} = Tlog\,(\frac{\text{SSE}}{T}) + (k+2)log(T)$$

As we have seen in the case of AIC, BIC also choose the model with the lowest of its value. But BIC penalizes extra predictors more than AIC. Hence, BIC tends to choose model with fewer predictors than AIC or AIC_c.

Among these three measures, some researchers prefer BIC. It is argued that if there is a true underlying model then BIC tends to select this model if there are enough observations (Hyndman & Athanasopoulos, 2021). It is standard practice to estimate these three measures where usually there is a consensus among these measures. In case the consensus breaks down, we resort to BIC for the final selection of the optimal model.

In Table 1, we present the value of these model selection criteria which helps us to find the optimal model for the data in use. We find there is consensus among all the measures and we find that Simple Exponential Smoothing (SES), comes up with the lowest value in all three measures. This is not surprising given the fact that there is little evidence of seasonality and trending behavior in the data as evident from

Figure 1. To increase our confidence in this assertion, we can scrutinize the data into further details such as yearly and seasonal pattern. .

Table 1: Values for different model selection criteria

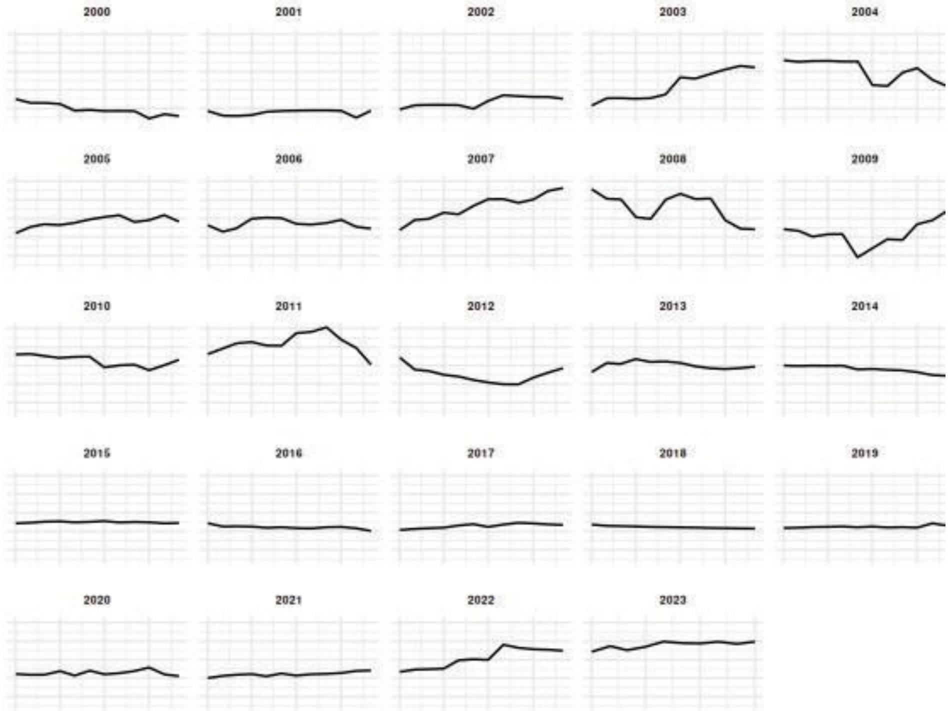
	Model selection criterion		
ETS models	AIC	AICc	BIC
No trend or seasonality			
Simple exponential smoothing	1407.5	1407.6	1418.4
Models with trend			
Holt's linear model	1411.5	1411.8	1429.8
Damped trend model	1412.7	1413.0	1434.6
Models with seasonality			
Holt-Winters' additive method	1438.9	1441.2	1501.1
Holt-Winters' multiplicative method	1485.4	1487.7	1547.6
Holt-Winters' damped method	1497.3	1499.9	1563.2

Source: Authors' calculation

4.1 Yearly pattern

In Figure 2, the inflation pattern in individual year has been plotted. Here we note that a high level of intra-year volatility coincides with volatility observed in the overall data in the corresponding periods (as observed in Figure 1). Additionally, we find no clear seasonal effect is evident considering all the individual yearly plots. Therefore, seasonality may not pose a significant concern in this context.

Figure 2: Overall year-wise inflation pattern

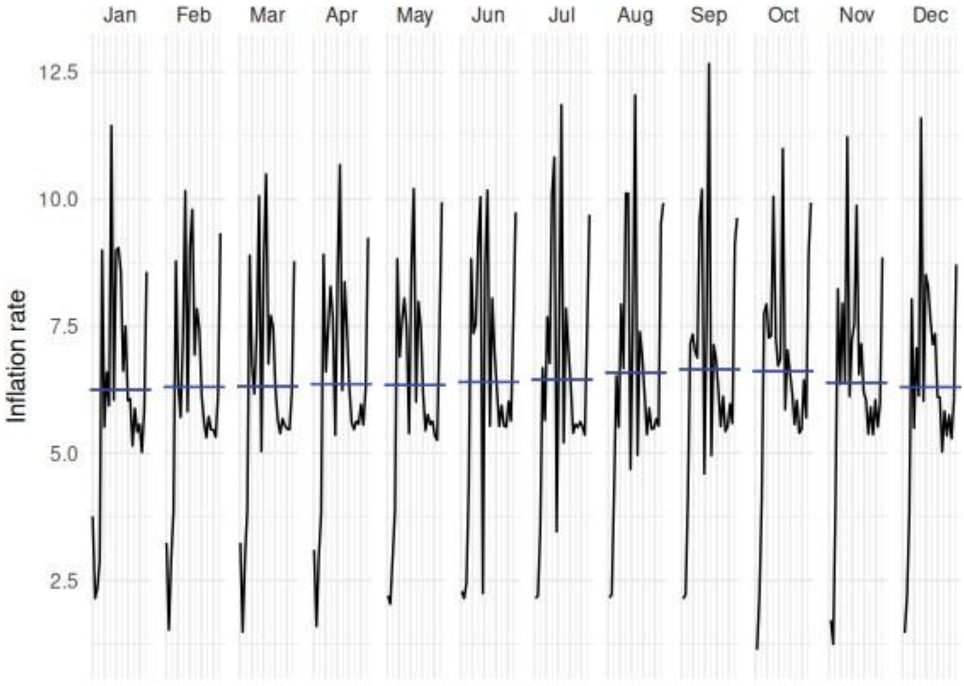


Source: Various editions of Economic Trends (Bangladesh Bank)

4.2 Seasonal subseries

Absence of seasonality can be further explored in Figure 3. In this figure, there is nothing particularly distinctive about any specific month. All twelve months exhibit remarkably similar patterns within themselves. For instance, in January, during the early 2000s, inflation was relatively low, peaked around 2010, again declined to a lower level, and then rose again from 2022 onwards. This general pattern repeats across almost every month. Consequently, apart from minor differences in mean value of inflation, there is minimal variation observed among these months.

Figure 3 Seasonal subseries of inflation pattern



Source: Various editions of Economic Trends (Bangladesh Bank)

From these visual depictions, it is evident that there is no apparent trend or seasonal pattern discernible in the data. Hence, considering the outcomes obtained from the previously discussed model selection criteria and the current visual examination, it is evident that SES models are appropriate for our purpose.

Although it appears that the SES model might be the optimal one given the data in question, we will inquire further to confirm it. To this end, in the next section will conduct an in-sample forecasting exercise to test which model offers the most accurate forecasting capabilities. Once optimal model is confirmed, that model will be used to derive out-of-sample forecasting for next two years.

5. Forecasting with ETS models

5.1 In-sample forecasting accuracy

The fact that Simple Exponential Smoothing (SES) minimizes all the model selection criterion is also exemplified by in-sample forecast accuracy measures as evident in Table 2. Prior to discussing this forecasting metrics, we will provide a brief overview of the three accuracy measures employed in this analysis.

Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are widely used metrics for evaluating the accuracy of forecasting models. MASE measures the relative performance of a forecast model against a naive benchmark, typically the naive seasonal method or the naive random walk method. It assesses the model's ability to outperform such simple benchmarks, providing insights into its effectiveness across different forecast horizons and time series patterns (Hyndman & Koehler, 2006). RMSE calculates the square root of the average squared differences between actual and forecasted values, providing a measure of the magnitude of errors in the same units as the original data (Willmott & Matsuura, 2005). MAE calculates the average of the absolute differences between actual and forecasted values, offering a straightforward measure of forecasting accuracy without considering the direction of errors (Dawson, 2018).

Table 2: In-sample forecasting accuracy

	Evaluation metrices		
ETS models	RMSE	MASE	MAE
No trend or seasonality			
Simple exponential smoothing	0.685	0.256	0.424
Models with trend			
Holt's linear model	0.685	0.257	0.425
Damped trend model	0.684	0.256	0.424
Models with seasonality			
Holt-Winters' additive method	0.689	0.266	0.441
Holt-Winters' multiplicative method	0.742	0.298	0.493
Holt-Winters' damped method	0.719	0.285	0.472

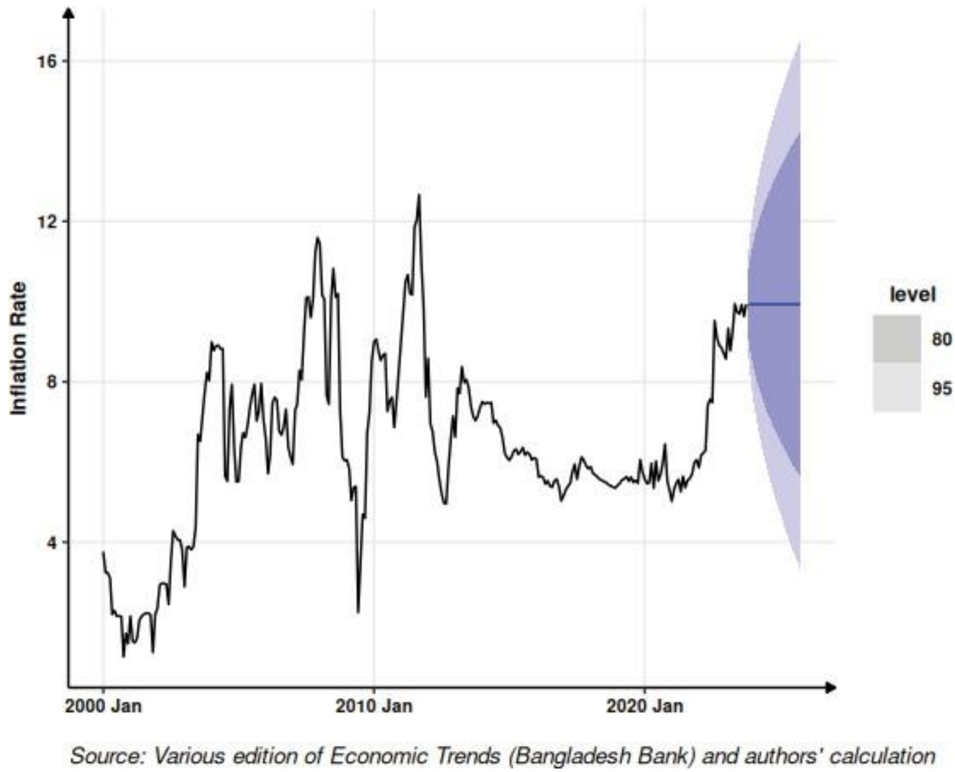
Source: Authors' calculation

In Table 2, a general observation is that models with seasonality are performing poorly compared with other models. This is not surprising since in our analysis we did not find any evidence of seasonality so far. Models without seasonality are providing results which are in close resemblance and the most similar results are generated by SES and damped trend models. We finally select these two models to produce out-of-sample forecasts presented in the next section.

5.2 Out-of-sample Forecasts

Firstly, we generate forecast with SES models along with their 80% and 95% confidence intervals which is presented in Figure 4. Not surprisingly, this forecast is generating a flat line indicating that in near future inflation rate may remain stable. In SES models, the general assumption is that there is no trend or seasonality in the observations. Therefore, it is natural to have a steady and relatively constant forecast in the near term.

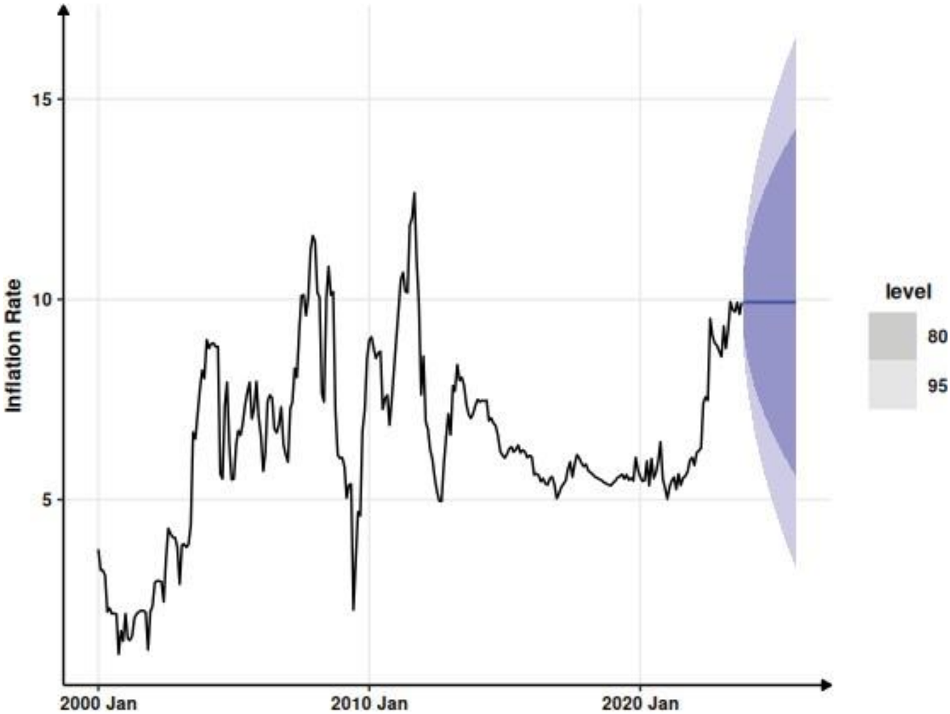
Figure 4: Out-of-sample (2 years) forecasts with SES



In Figure 5, Damped trend model also produces similar type of forecasts as SES. This is expected since damped trends essentially use decreasing trends which may produce the same forecasts as a model with no trend.

We have to note that even though we have found almost identical results for the above two models, there are certain advantages in using Damped Trend models. The enhancement in Damped Trend model enables the model to capture short-term fluctuations while gradually converging towards a stable trend, making it particularly effective for data exhibiting both short-term volatility and long-term stability (Hyndman & Khandakar, 2008). While SES offers simplicity and ease of interpretation, the Damped Trend model provides additional flexibility, making it preferable for forecasting scenarios where both short-term dynamics and long-term trends are significant considerations (Harrison, 2016). Ultimately, the choice between these models hinges on the specific characteristics of the data and the forecasting objectives at hand.

Figure 5: Out-of-sample forecasts (2 years) using Damped trend model



Source: Various edition of Economic Trends (Bangladesh Bank) and authors' calculation

6. Discussion and Conclusion

In the above, we discussed the evaluation of Simple Exponential Smoothing (SES) and other forecasting models using three accuracy measures: Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). These metrics assessed the effectiveness of the models in comparison to a naive benchmark, the magnitude of forecast errors, and overall accuracy. These results show that models without seasonality, particularly SES and the damped trend model, produce very similar results in terms of forecasting accuracy, while models with seasonality perform poorly due to the absence of seasonal patterns in the data (Lidiema, 2017; Ofori & Ephraim, 2012). From these findings, we can conclude that SES and the damped trend model are the most suitable for generating out-of-sample forecasts, as they both indicate a stable inflation rate in the near future. SES assumes no trend or seasonality, leading to flat, constant forecasts, while the damped trend model captures short-term fluctuations before converging towards a stable trend. This makes the damped trend model more flexible and advantageous when both short-term volatility and long-term stability are significant considerations (Hyndman et al., 2008).

Despite the similarities between SES and the damped trend model, the choice of model depends on the specific characteristics of the data and the forecasting goals. Another feature of these models is the limited exploration of seasonal models. While the restricted performance of these models is acknowledged, the study does not explore whether deeper analysis or alternative methods could uncover hidden seasonal patterns in the data. Another area where the study could improve is in addressing forecast uncertainty. While confidence intervals are provided, there is limited discussion of how uncertainty impacts decision-making. There is scope to explore more sophisticated methods, such as Bayesian forecasting or probabilistic models, to better quantify and communicate the risks associated with forecasts. Additionally, incorporating exogenous variables like interest rates or global economic factors into the forecasting models could provide more accurate predictions in complex economic environments where inflation or other variables are influenced by external factors which we could not explore due to data limitations. While there has been extensive ARIMA modeling conducted worldwide to forecast macroeconomic variables like inflation, relatively few studies have utilized ETS methods for forecasting. ETS methods are known to be more user-friendly for practitioners and provide more accurate forecasts in some cases than ARIMA. But studies on ETS methods is non-existent in forecasting literature of Bangladesh. To address this, this paper examines various ETS methods and determines that SES and Damped trend models are the most effective in terms of model selection and forecast accuracy for inflation data (Okereke & Bernard, 2014; Faisal, 2012). The policy implications of this study are significant, particularly in areas such as economic forecasting, inflation monitoring, and resource allocation. The findings suggest that Simple Exponential Smoothing (SES) and Damped Trend models are well-suited for stable economic environments where no strong trends or seasonal fluctuations are present, such as the near-term inflation forecasts presented in the study (Holt and Winters, 1960). Policymakers can leverage these models for short-term, low-volatility scenarios to project economic indicators like inflation rates, allowing for more informed fiscal and monetary policy decisions. However, the study also highlights the limitations of SES when dealing with more complex economic patterns involving short-term volatility or structural shifts (Hyndman et al., 2008). In such cases, Damped Trend models offer greater flexibility and adaptability, enabling policymakers to react to short-term economic fluctuations while keeping an eye on long-term stability. Therefore, when crafting policies aimed at managing inflation or similar economic variables, the choice of forecasting model should align with the specific economic conditions—using simpler models like SES for steady-state conditions and more dynamic models like the Damped Trend method when dealing with economic volatility or transitional phases. This nuanced approach can help in optimizing resource allocation and enhancing the accuracy of economic planning.

The study's reliance on Simple Exponential Smoothing (SES) and Damped Trend models, while useful for specific contexts, limits the scope of model comparison. Future research could expand to include more sophisticated time series models, such as ARIMA, SARIMA, or even machine learning-based approaches like Long Short-Term Memory (LSTM) networks. These models may offer improved performance, especially for complex datasets with non-linear patterns, trends, and seasonality (Harrison, 2016). Furthermore, the assumption that the time series has no trend or seasonality constrains the study's applicability to dynamic environments where economic shifts or structural breaks occur. These limitations call for further exploration of models that can handle such complexities, including regime-switching models that adapt to different economic conditions. By addressing these shortcomings, future research could build on the current findings to improve forecasting accuracy and provide more robust insights for policymakers, especially in volatile or rapidly changing economic conditions. Hybrid models that combine different forecasting approaches could also offer more flexibility, capturing both short-term trends and long-term patterns more effectively. Ultimately, future studies should aim to enhance the generalizability and practical utility of forecasting models by focusing on a broader range of models, out-of-sample performance, and more nuanced approaches to uncertainty.

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