Consumer Price Index Prediction by ARIMA And ETS

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Abstract. Consumer Price Index (CPI) is one of the most widely used indicators to measure inflation and reflect changes in the cost of living. Accurate forecasting of CPI has become increasingly important as it provides essential guidance for economic decision-making and financial planning. This paper applies two classical time series approaches, the ARIMA model and the ETS model, to monthly CPI data, with the aim of comparing their forecasting performance. The results show that both models capture the upward trend of CPI, while the ARIMA (2,1,2) with drift produces slightly lower RMSE, MAE, and MAPE values than ETS (A, A, N), suggesting that ARIMA has marginally better predictive accuracy. These findings confirm the effectiveness of both methods in modeling CPI but also indicate that ARIMA provides a more precise fit. The study contributes to the literature by offering an updated evaluation of CPI forecasting methods, which may support future empirical work and provide references for policy and market analysis.

Keywords: Consumer Price Index (CPI); ARIMA; ETS; time series forecasting.

1. Introduction

The Consumer Price Index (CPI) is widely regarded as one of the most important macroeconomic indicators because it reflects the overall price level of goods and services, shaping monetary policy and influencing both investment decisions and household welfare. Accurate CPI measurement and forecasting are important for keeping the economy stable and for helping both policymakers and the public make better financial decisions [1].

Many researchers have examined different methods to improve the accuracy of CPI forecasting. Some recent studies have used high-frequency data to enhance prediction results, while others have analyzed how shifts in consumer spending during the pandemic affected inflation measurement [2]. In addition, several papers have applied ARIMA models to specific countries, such as Iraq and the Philippines [3-5]. Comparative research has also discussed the strengths and limitations of both ARIMA and ETS models in forecasting practice [4]. U.S. evidence from official sources shows that fixed-weight CPI measures understated inflation at the pandemic onset due to rapid expenditure shifts [6-7]. Micro data from the U.S. CPI further indicate a post-pandemic rise in the frequency of price changes, underscoring structural changes in price-setting behavior [8]. Beyond traditional models, behavioral factors such as investor attention have also been shown to affect CPI inflation forecasts, while recent studies examine whether deep learning methods can outperform machine learning and statistical models in inflation forecasting [9-10]. While these studies provide valuable insights, most of them are concentrated in the pre-pandemic or early pandemic context. Since the global economy has undergone structural changes after COVID-19, research on post-pandemic CPI dynamics remains relatively scarce [6].

This study addresses this gap by using time series data to evaluate the forecasting performance of ARIMA and ETS models in predicting CPI. By comparing model outputs with actual data, the paper aims to provide evidence on which approach performs better in the post-pandemic setting. This contributes to the literature on CPI forecasting and offers practical reference value for economic monitoring and decision-making.

2. Data

The dataset used in this paper is the U.S. Consumer Price Index (CPI), obtained from the Federal Reserve Economic Data (FRED) database. The selected period makes it possible to compare the pre-pandemic years (2010–2019) with the pandemic years (2020-2022), when economic changes become more noticeable. Fig. 1 presents the movement of the U.S. Consumer Price Index (CPI) from January 2010 to December 2022. The index shows a general upward pattern, with a faster rise during the years affected by the pandemic after 2020. Because the data were already given on a monthly basis, no resampling was needed. The series was divided into two parts for analysis: the training period from 2010 to 2019, which reflects the situation before the pandemic, and the test period from 2020 to 2022, which reflects the changes that occurred during the pandemic. This separation helps assess how well the forecasting models perform in both normal and unstable economic conditions.

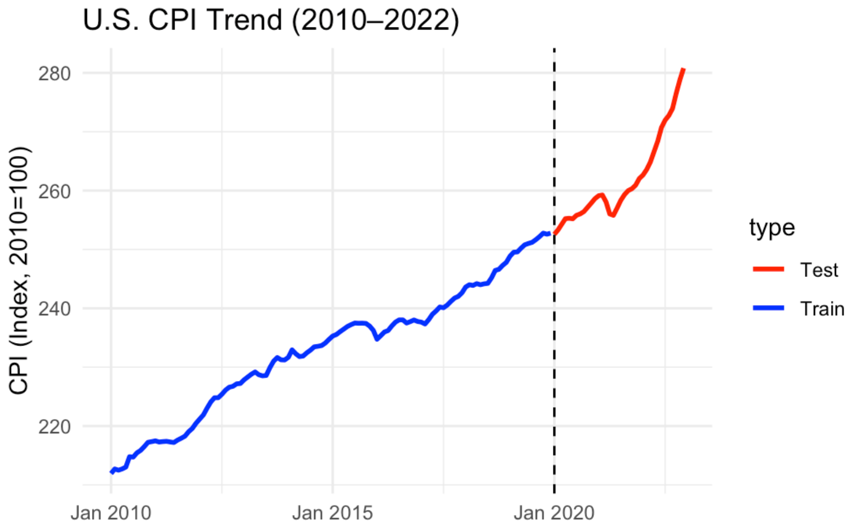

Fig. 1 CPI

3. Method

3.1. ARIMA model

CPI data usually changes gradually over time, and the current value is often related to the values from previous months. Because of this persistence, ARIMA models are suitable for describing and forecasting CPI movements. The model works by combining three parts: autoregression, differencing, and moving average. When the original series is not stable over time, the differencing step helps make it more consistent. These features make ARIMA a useful approach for predicting CPI, as it can handle both long-term trends and short-term fluctuations.

The ARIMA model, written as ARIMA (p, d, q), includes three parameters that describe its main components: the autoregressive part (AR), the differencing order (I), and the moving average part (MA). It is commonly used for time series that show patterns or gradual changes instead of random noise. The general form of the model can be written as follows:

$$y_t = c + \phi_1 B_{y_t} + \cdots + \phi_p B^p y_t + \varepsilon_t + \theta_1 B_{\varepsilon_t} + \cdots + \theta_q B^q \varepsilon_t \tag{1}$$

In the ARIMA model, y_t denotes the observed value of the time series at time t, and c is the constant term that shifts the meaning of the process. The autoregressive coefficient ϕ_p captures the extent to which past values influence the current observation, while the backshift operator B is defined such that $B^k y_t = y_{t-k}$. The random error term ε_t represents white noise at time t. The moving average coefficient θ_j reflects the impact of past errors on the current value, and q specifies the order of the moving average process, indicating how many past error terms are incorporated into the model.

3.2. ETS model

The CPI series usually contains a clear trend over time, reflecting long-term inflation. ETS models are well suited because they directly handle level and trend components, and can also include seasonality if needed. By adjusting smoothing parameters, ETS can capture gradual changes without overfitting short-term noise. For this reason, ETS is appropriate for CPI, especially when the focus is on stable forecasting of inflation patterns.

The ETS framework is based on exponential smoothing with components for Error (E), Trend (T), and Seasonality (S). In this study, the selected specification is ETS (A, A, N), meaning additive error, additive trend, and no seasonality. The general structure is:

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \tag{2}$$

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha_{\varepsilon_t} \tag{3}$$

$$b_t = b_{t-1} + \beta_{\varepsilon_t} \tag{4}$$

$$s_t = s_{t-m} + \gamma_{\varepsilon_t} \tag{5}$$

In the ETS model, y_t denotes the observed value of the time series at time t, while ℓ_t represents the level or baseline of the series. The trend component is denoted by b_t, reflecting whether the series is increasing or decreasing over time, and the seasonal component is denoted by s_t, capturing recurring patterns with a period of length m. The random error term ε_t accounts for white noise in the series. The smoothing parameters α , β, and γ correspond to the level, trend, and seasonality, respectively, and together regulate how new information is incorporated into the model. Collectively, these elements define the ETS structure for time series forecasting.

4. Results

When working with time series data, it is common to divide the dataset into two parts: one for training and one for testing. The training set is used to estimate model parameters, while the test set is applied to evaluate how well the model performs on unseen data. In this paper, data from 2010 to 2019 is treated as the training set, and data from 2020 to 2022 is treated as the test set. The parameters obtained from the training data are summarized in Table 1.

Table 1. Parameter Fitting Results

	Parameter 1	Parameter 2	Parameter 3
ARIMA	2	1	2
ETS	A	A	N

As shown in Table 1, the models selected are ARIMA (2,1,2) with drift and ETS (A, A, N). For ARIMA (2,1,2), the first parameter p=2 indicates that the model incorporates two lagged values of CPI. The second parameter d=1 means that the series is differenced once to remove the trend and achieve stationarity. The third parameter q=2 shows that the model includes two past error terms to refine forecasting accuracy. The drift component allows the model to capture a steady long-term change in the CPI.

For the ETS (A, A, N) model, the first “A” specifies that errors enter the model additively. The second “A” shows that the trend is modeled additively, representing a linear growth pattern. The final “N” indicates the absence of seasonality. This makes ETS (A, A, N) appropriate for the CPI data, which displays a clear upward trend but no pronounced seasonal cycle. The fitting results of ARIMA and ETS are shown in Fig. 2 and Fig. 3, respectively.

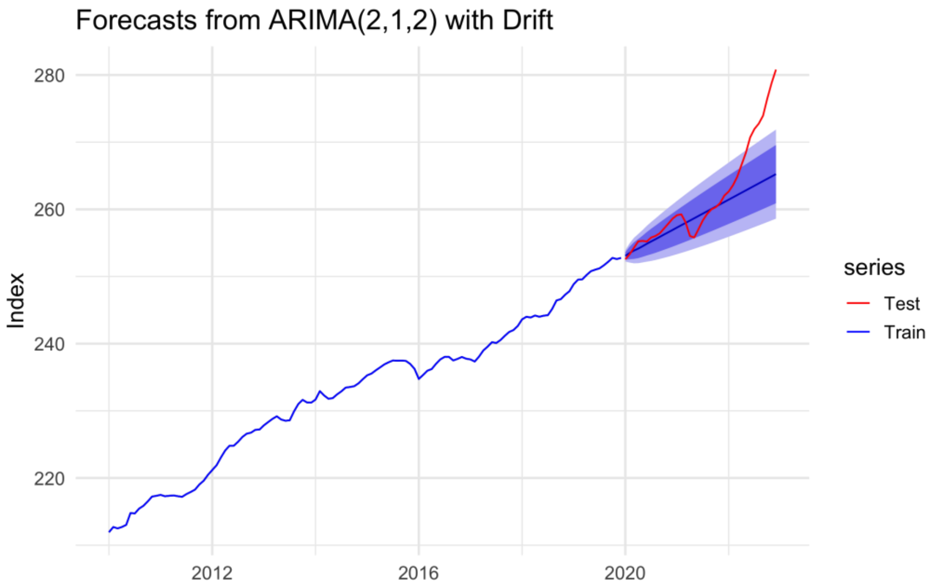

Fig. 2 ARIMA Result

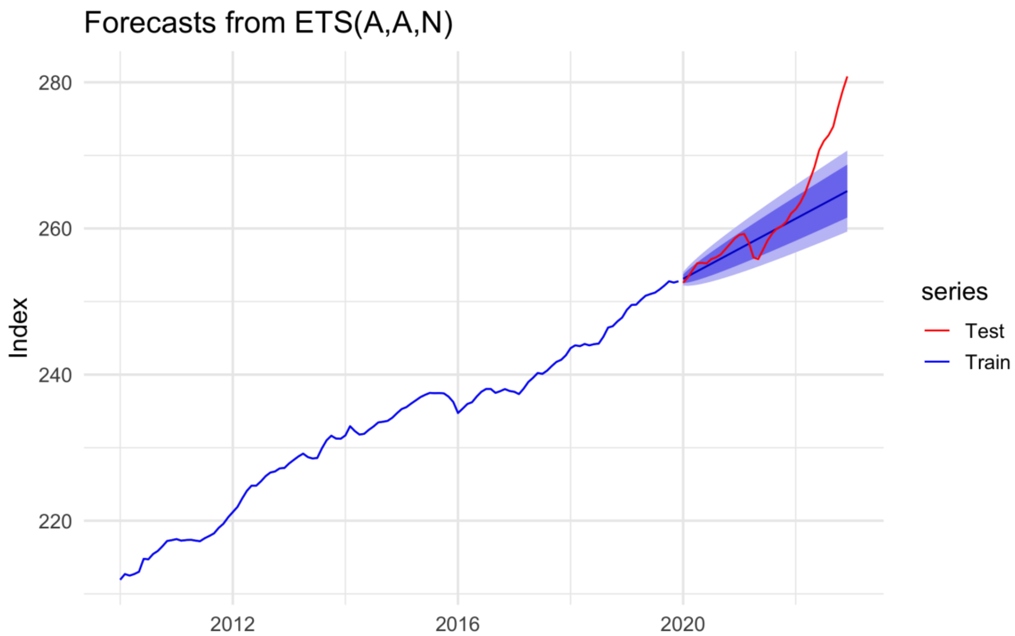

Fig. 3 ETS Result

By comparing Fig. 2 and Fig. 3, it can be seen that both the ARIMA (2,1,2) model with drift and the ETS (A, A, N) model produce forecasts that follow the actual upward trend of the CPI. The predicted lines in both models extend smoothly from the training set into the testing period and capture the overall direction of the series. While there are slight differences in the shape of the forecast intervals, the general patterns are consistent, as both models point to a steady increase. This suggests that the two methods provide broadly similar results, and further accuracy evaluation is needed to determine which model performs better. Table 2 shows the accuracy of ARIMA and ETS model predictions.

Table 2. Comparison Results

Model	RMSE Results	MAE Results	MAPE Results
ARIMA	5.2088	3.1584	1.1665
ETS	5.2667	3.2050	1.1839

According to Table 2, the ARIMA (2,1,2) model with drift gives slightly lower RMSE, MAE, and MAPE values than the ETS (A, A, N) model. This indicates that the ARIMA model provides somewhat better forecasting accuracy for CPI. Although the difference between the two models is small, ARIMA appears to capture the actual CPI trend more effectively.

5. Conclusion

The results of this study show that both the ARIMA and ETS models work well for forecasting the Consumer Price Index. When applied to monthly CPI data, both methods can describe the overall upward trend of prices, especially during periods of economic change. Among the two, the ARIMA (2,1,2) model with drift performs slightly better, as it gives lower RMSE, MAE, and MAPE values, suggesting a closer match to the actual data. These findings suggest that traditional time series models are still helpful for understanding CPI movements and can offer useful references for economic forecasting and later research.

Although the analysis provides meaningful results, it also has several limitations. The models used in this paper are linear and do not include outside variables, which may limit their ability to capture sudden or nonlinear changes in inflation. Moreover, the dataset only covers data up to 2022, so recent developments in global markets are not reflected. Future research could build on this work by adding newer data, testing other forecasting methods, or including macroeconomic indicators to improve prediction results.

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