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A Machine Learning Framework for Forecasting Inflation (CPI-U) in the United States

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Abstract: This study fitted the Consumer price index for urban Consumer (CPI-U) in USA using a time series data. A comparative evaluation of 27 Machine learning Models for time series data has been carried out **.** ETS Model was found to be best fit to the data .The Performance of the Models were assessed by the three matrices : Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) . It offered a two-year projection for the anticipated CPI-U. The two-year forecast, which runs from January 2024 to December 2025, was finally made. According to the study, there are slight variations in CPI-U throughout each year, indicating potential seasonal fluctuations. For example, from January to July in both 2024 and 2025, there is a steady increase in the it, which then stabilizes or slightly fluctuates in the latter half of each year. This may reflect seasonal changes in consumer spending, supply chain variations, or other economic factors that affect prices.

Keywords: ETS, LSTM, CNN, RNN, DEEP LEARNING, RMSR, MAPE, MAE

Introduction

The monthly variation in prices that American consumers pay is tracked by the Consumer Price Index (CPI_U). The CPI_U is determined by the Bureau of Labour Statistics (BLS) using a weighted average of prices of eight major groups (food and beverages, housing, apparel, transportation, medical care, recreation, education and communication, and other goods and services) that people buy for day-to-day living. It also includes government-charged user fees like water and sewerage charges. A

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metric called the consumer price index (CPI-U), base 1982-1984 equals 100 for urban consumers looks at the weighted average of the prices of a basket of goods and services, including food (13.7%), energy (6.6%), all other Items (79.7%) that are indicative of all consumer spending in the United States. Based on 80,000 monthly price quotes from 23,000 retail and service businesses as well as 50,000 rental housing units, it is a commonly used indicator of inflation. It assesses changes in shelter expenditures, including those for owner-occupied dwellings, and includes 93% of the US population. When deciding on economic policy, the Federal Reserve looks at CPI data and modifies the Fed funds rate in response to inflation rates that are higher than intended. The consumer price index (CPI-U) has a major impact on a country's economic pricing system. It is an essential instrument for budgetary.The paper is structured as follows; (i) Introduction, (ii) Review of literature, (iii) Methodology & Modeling, (iv) Sources of data, (iv) Empirical Results the lastly (vi) Conclusions.

Review of Literature

The set of quantitative observations placed chronologically is called a time series. Over the past three decades, time series analysis has garnered a lot of attention (Kam, Kin Ming, 2014). In the past, people have typically assumed that time is a continuous or discontinuous variable and that the dependent variables cannot be compared (Hyndman, Rob J., and George Athanasopoulos). The kind of dataset that is used to train models determines how time series forecasting models are constructed. Compared to non-stationary datasets, stationary datasets are simpler to train for prediction. In actuality, transforming a non-stationary dataset into a stationary dataset is essential (Manuca, Radu, and Robert Savi,1996). Models were able to comprehend stationary datasets with ease and extract information from them more effectively.

Python has a wide range of models that are used for value prediction. Deep neural networks and supervised machine learning models are utilised for forecasts. Without being specifically coded, supervised machine learning gives systems the potential to learn from data automatically and improve with experience (Choudhary, Rishabh, and Hemant Kumar Giane, 2017). In a similar vein, deep networks find use in a wide range of domains such as creation, detection, and prediction. When it comes to forecasting, deep neural network models outperform machine learning algorithms .

Deep learning architectures are a pretty fresh and modern method for predicting the Consumer Price Index. The effectiveness of artificial intelligence algorithms to forecast the post sample of time series data has previously piqued the interest of scholars. Deep neural network topologies provide the best explanation for the nonlinear data structures. Applications of deep learning algorithms for stock price prediction have been tested in a number of studies (Kwong, 2001; Nygren, 2004; Huang et al., 2007). A small number of researchers have also demonstrated that deep learning algorithms are superior for predicting financial data (Hossain et al., 2008; Qian, 2017; Selvin et al. 2017). According to recent research, certain deep learning algorithms (such as CNN-LSTM) should be used for the prediction. The prediction efficiency of three specific machine learning models—Logistic Regression, Support Vector Machine, and Multilayer Perceptron—was compared with the historical time series model ARIMA by Qian et al. (2017). They highlighted that machine learning models, an emerging field of research in recent years, may prove to be superior than traditional models using the S&P 500 as an example. They believe that future researchers should attempt to use long-short term memory networks (LSTM) to anticipate time series data. Kambo b s (2019) in their study on Modeling Consumer Price Index of India for Urban Consumers found that the ARIMA (0, 1, 1) X (0, 1, 1) 12 is best fitted to CPI data for Urban Consumers for the period from January 1990 to January 2019. Kambo b s (2020) et.al in their paper on forecasting end of covid 19 in India found that ARIMA (0, 1, 1) and Holt exponential smoothing Models are best fit for active and removed rates respectively. Selvin et al. (2017) forecasted the values of three stocks—Infosys, TCS, and Cipla—listed on the National Stock Exchange using a sliding window technique and various deep learning algorithms. Deep learning architectures that are utilized invariantly include Recurrent Neural Network, Convolutional Neural Network. Selected companies from the Dhaka Stock Exchange were selected for analysis using the following prediction methods: Random Forest, Feed Forward Neural Network, Support Vector Machine, and Back-propagation. The outcomes showed that when it comes to stock price prediction, RNN with LSTM performs better than machine learning techniques. The daily trading performance of several equities predicted by six conventional machine learning algorithms and six sophisticated deep neural network algorithms was compared by Lv et al. (2019). Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes model (NB), Classification and Regression tree (CART), and Extreme Gradient Boosting method (XGB) are some examples of machine learning techniques. Chen et al. (2021) explored the application of deep learning algorithms in trading. They used the Long-Short Term

Memory (LSTM) neural network architecture and forecasted the stock prices of Intel Corporation (NASDAQ: INTC). The study suggested that various architectures of LSTM could be explored with the different number of neurons and layers. Sen et al. (2021) used Long Short-Term Memory neural network architecture for the prediction of stock prices taking daily data (Close price) of 70 Companies listed in National Stock Exchange India. The study revealed that LSTM proved to be highly accurate and prediction of stock prices data. For the purpose of prediction, six long short-term memory neural network algorithms and four convolutional neural network algorithms were employed. A unique method called Multi Step Forecasting with Walk-Forward validation was used to test the models. According to this study, CNN algorithms perform better than LSTM algorithms.

Source of Data

The data on Consumer price index for urban consumers (CPI-U) from January 2001 to December 2023 used in this research work, has been extracted from the Websites: www.bls.gov US Bureau of Labor Statistics (BLS). It is the monthly data with base year 1982-84.

Methodology and Modeling

The data was analyzed by fitting 27 models using PYCART (version 3.4) package for time series.

Functioning of the Machine learning Models generally involve the following steps:

1. Important Libraries : Down loads necessary Libraries such as Pandas, NumPy, Matplotlib, Seaborn sklearn, and pycaret, karas and tensor flow.
2. Data cleaning : Data Understanding, handling missing values, removing duplicates, Feature Scaling, Handling categorical variables: Outlier detection and treatment, Feature engineering and Data transformation
3. Data Splitting : we generally split the dataset into training (80 %) and testing (20%) sets. The testing set was used to evaluate the performance of the Models .
4. Models selection : selecting appropriate Models from sk learn and PyCaret library
5. Model Training : Train the machine learning models on training data set.
6. Model Evaluation : The model's performance on testing data using appropriate

evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and R Square(R^2) were employed to estimate the accuracy of the forecast algorithms.

7. Model Comparison : Compared the performance of the models to determine which one provide better results .

Twenty-seven Machine learning models were fitted to the CPI-U time series data, it has been observed that ETS model was found to be best fit model to CPI-U data.The ETS model, which stands for Error, Trend, Seasonality, is a statistical forecasting model used primarily in time series analysis. Unlike many machine learning models that learn from data through flexible algorithms, the ETS model is more of a classical approach that explicitly models time series components to make accurate forecasts.

I. Key Features of the ETS Model

1. Error (E): The error component represents the nature of the errors in the data. It could be additive (A) or multiplicative (M). The choice affects how the errors in the time series are modelled :
   - Additive (A): The errors are constant over time, regardless of the level of the series.
   - Multiplicative (M): The errors change proportionally to the level of the series (i.e., larger errors for larger values).

2. Trend (T): The trend component captures any systematic upward or downward movement in the data over time. It can also be:
   - None (N): No trend.
   - Additive (A): A linear trend is added to the series.
   - Multiplicative (M): A linear trend is multiplied by the series.
   - Damped (Ad or Md): A trend that gradually flattens out over time (either additive or multiplicative).

3. Seasonality (S): The seasonality component models the repeating short-term cycles in the data, such as monthly or quarterly patterns. It can be:
   - None (N): No seasonal pattern.
   - Additive (A): Seasonal changes have a constant magnitude.
   - Multiplicative (M): Seasonal changes have a changing magnitude proportional to the level of the series.

The combination of these components defines the type of ETS model. For example, an ETS(A, Ad, A) model has an additive error, a damped additive trend, and an additive seasonal component.

II. Formula for the ETS Model

The general ETS model can be expressed as:

$$y_t = (l_{t-1} + b_{t-1}).s_{t-m} + e_t$$

Where:

y_t is the observed value at time t

l_t is the level(mean) component at time t.

b_t is the trend component at time t.

s_t is the seasonal component at time t.

e_t is the error term at time t.

m is the number of observations per season (e.g., 12 for monthly data in one year).

The above model adjusts the level, trend, and seasonality components according to their types (additive or multiplicative).

Advantages of the ETS Model

- **Interpretability:** The ETS model is highly interpretable because it explicitly decomposes a time series into three meaningful components: Error, Trend, and Seasonality.
- **Flexibility:** It can handle different combinations of components (E, T, S), making it suitable for a wide range of time series data with varying properties.
- **Suitability for Forecasting:** The ETS model performs well in situations where time series data have clear patterns, trends, or seasonal effects.

Limitations of the ETS Model

- **Limited to Time Series:** The ETS model is specifically designed for time series forecasting, so it is not suitable for other types of machine learning problems.
- **Assumes Linear Relationships:** It assumes linear relationships in trends and seasonality, which might not be ideal for all-time series data, especially those with non-linear patterns.

Not Robust to Outliers: The model can be sensitive to outliers unless special adjustments are made.

Empirical results and discussions

Statistical Descriptions of data

Shapiro-Wilk test, Ljung-Box Test and ADF (Augument Dickey-Fuller) test were used to test the normality, white noise, and stationarity of CPI-U time series espectively.

Shapiro-Wilk test was applied to checks weather the CPI-U data follows a normal distribution. Since the p-value is significantly lower than 0.05 and even 0.01, it strongly suggests that the data does not follow a normal distribtion.

The Ljung-Box test checks whether a time series is "white noise," meaning that it has no significant autocorrelation at various lags, implying randomness and no predictable patterns.

The null hypothesis Ho : CPI-U time series data is white noise (i.e., no significant autocorrelations) against altrenative Hypothesis H1: that it has significant autocorrelations.

It has been observed that the p-value from the Ljung-Box test is 0.0000001 (or very close to zero). Since this p-value is less than 0.01 (even stricter than the typical 0.05 level), We reject the null hypothesis with 99% confidence. A p-value of zero implies that the observed autocorrelations are highly unlikely to occur by random chance alone. This suggests that the CPI-U data has significant patterns or dependencies between its values at different points in time. The very low p-value confirms that the CPI-U data exhibits significant autocorrelations and is not purely random.This could indicate the presence of trends, cycles, or other patterns within the data that are not explained by chance.

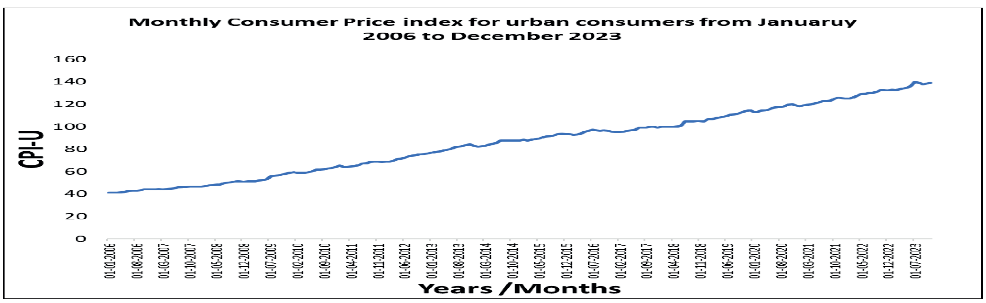

Figure 1

Monthly Consumer price index for the Urban Consumers from January 2001 to December 2023 (base 1982-1984 = 100) are shown in the (Figure I).The increasing trend of CPI-U clearly indicates that CPI-U time series data has linear trend as well as liner seasonal trend and is not stationary . It is further confirmed by as the p value for ADF test for stationary is 0.98 which is significantly greater than 0.01.The Machine learning models have the assumpton that time serires must be stationary.CPI-U data is transformed by taking non - seasional difference (d =1). Plot of the transformed series (Figure 2) which clearly shows that the time series is now stationary.

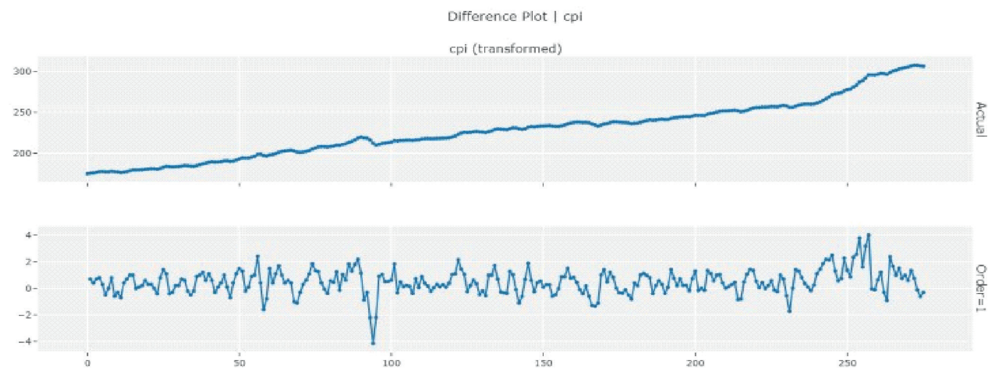

Figure 2

Out liers were absent in the data as clear from box plot (Figure 3).

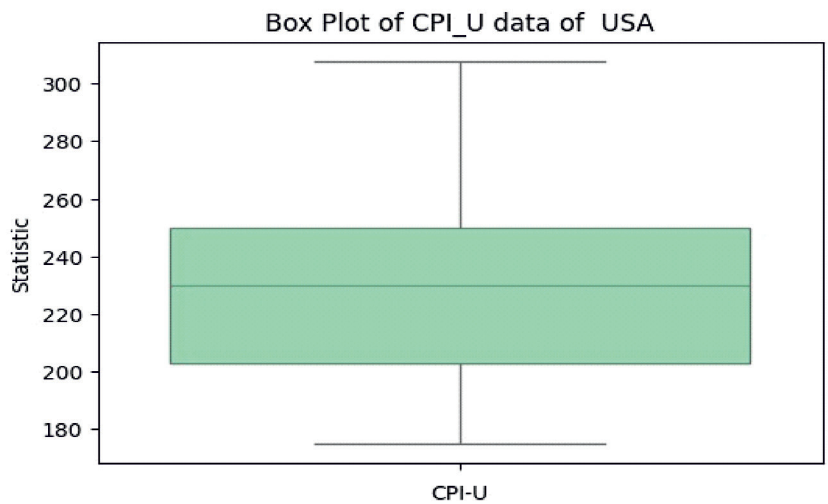

Figure 3

Table 1 Comparision of performance of Machine learning models for Consumer Price Index in USA

Sl No.	Model	MAE	RMSE	MAPE
1	ETS	3.5398	4.4169	0.0129
2	Exponential Smoothing	3.562	4.4276	0.013
3	ARIMA	5.2185	5.8452	0.0188
4	Huber w/ Cond. Deseasonalize & Detrending	5.7906	6.6339	0.0206
5	Orthogonal Matching Pursuit w/ Cond. Deseasonalize & Detrending	5.9151	6.7471	0.021
6	Linear w/ Cond. Deseasonalize & Detrending	6.1956	7.1262	0.0219
7	Ridge w/ Cond. Deseasonalize & Detrending	6.208	7.1369	0.022
8	Bayesian Ridge w/ Cond. Deseasonalize & Detrending	6.2111	7.1394	0.022
9	Auto ARIMA	6.4343	7.1529	0.0227
10	Theta Forecaster	6.4789	7.5337	0.0228
11	AdaBoost w/ Cond. Deseasonalize & Detrending	7.0607	7.9005	0.025
12	STLF	7.291	7.961	0.0258
13	Elastic Net w/ Cond. Deseasonalize & Detrending	7.6081	8.5796	0.0267
14	Lasso w/ Cond. Deseasonalize & Detrending	7.8823	8.8918	0.0276
15	Lasso Least Angular Regressor w/ Cond. Deseasonalize & Detrending	7.8823	8.8918	0.0276
16	Random Forest w/ Cond. Deseasonalize & Detrending	8.3758	9.3232	0.0296
17	Light Gradient Boosting w/ Cond. Deseasonalize & Detrending	8.7105	9.6552	0.0307
18	Naive Forecaster	8.7933	9.7195	0.031
19	K Neighbors w/ Cond. Deseasonalize & Detrending	9.0469	10.0569	0.0315
20	Gradient Boosting w/ Cond. Deseasonalize & Detrending	9.4226	10.5237	0.0331
21	Extreme Gradient Boosting w/ Cond. Deseasonalize & Detrending	9.4293	10.7262	0.0332
22	Extra Trees w/ Cond. Deseasonalize & Detrending	9.5911	10.6345	0.0337
23	Decision Tree w/ Cond. Deseasonalize & Detrending	9.7858	10.6439	0.0342
24	Polynomial Trend Forecaster	10.257	10.8442	0.0358
25	Seasonal Naive Forecaster	12.3325	12.7885	0.0436
26	Croston	13.9244	14.5892	0.0492
27	Grand Means Forecaster	54.325	54.5081	0.1962

The comparative Performance of the 27 machine learning algorithms on training data (Table 1) were assessed by the three matrices viz. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) The most important measure of goodness of fit of models is Root mean square error(RMSR) ·It has been observed that RMSR for ETS model is minimum among all the 27 models compared. Figure 4 explicitly indicates that the predicted and actual CPI-U are very close to each other.

From the above discussion it is inferred that ETS model is best and can be deployed to predict the Consumers Price index for Urban Consumers in USA.

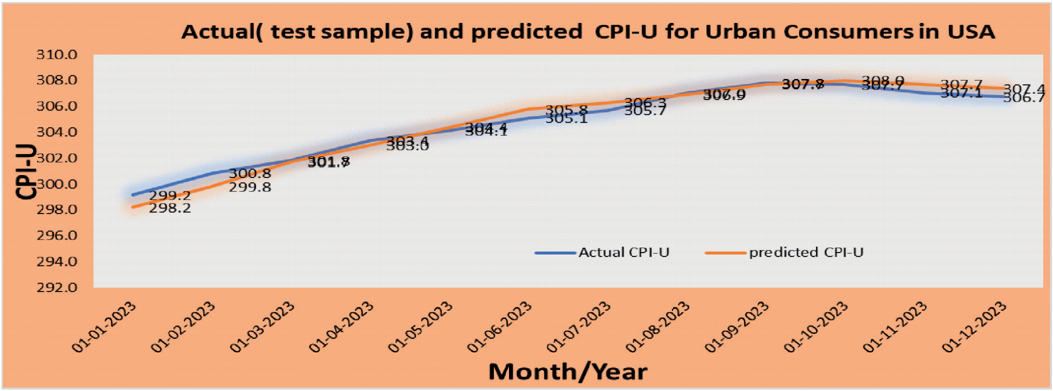

Figure 4

The two years forecasting of from January 2024 to December 2025 are shown in the Table 2

Table 2 : Predicted Consumer Price Index urban consumers in USA from January 2024 to December 2025

Month	*CPI-U*		
	2023	*2024*	*2025*
January	299.2	308.1	317.5
February	300.8	309.7	319.1
March	301.8	311.4	320.9
April	303.4	312.7	322.2
May	304.1	314.0	323.4
June	305.1	315.2	324.7
July	305.7	315.6	325.1
August	307.0	316.1	325.6
September	307.8	316.8	326.3
October	307.7	317.0	326.5
November	307.1	316.6	326.0
December	306.7	316.1	325.5
Annual Average	304.7	314.1	323.6

The table provides the predicted Consumer Price Index for All Urban Consumers (CPI-U) in the USA from January 2024 to December 2025, along with an average for each year.

1. Overall Trend
   - **CPI-U Growth**: The table shows a general upward trend in the CPI-U from 2023 to 2025. The CPI-U represents the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. This increase indicates that consumer prices are expected to rise steadily over the next two years.
   - **Annual Increase**: The average CPI-U increases from **304.7** in 2023 to **314.1** in 2024, and further to **323.6** in 2025. This represents an approximate **3.1% increase** from 2023 to 2024 and another **3.0% increase** from 2024 to 2025, suggesting consistent inflationary pressures.
2. Monthly Variations
   - **Seasonal Patterns**: There are slight variations in CPI-U throughout each year, indicating potential seasonal fluctuations. For example, from January to July in both 2024 and 2025, there is a steady increase in the CPI-U, which then stabilizes or slightly fluctuates in the latter half of each year.

Possible Reasons for CPI-U Increase from January to July

(a) **Post-Holiday Spending Recovery**: After the holiday season in December, consumer spending typically slows down in January. However, as the year progresses, consumer confidence and spending often increase, particularly due to New Year resolutions, promotions, and clearance sales in the retail sector. This can contribute to higher demand for goods and services, pushing prices upward.

(b) **Tax Refund Season**: In the USA, many consumers receive tax refunds between February and April. These refunds can boost consumer spending on various goods and services, creating increased demand in the economy. As demand rises, businesses may increase prices, contributing to a gradual rise in the CPI-U during these months.

(c) **Seasonal Demand for Certain Goods and Services**: From spring to early summer (March to July), there is typically increased demand for seasonal goods such as clothing, household items, and outdoor equipment. Additionally, service sectors like travel, hospitality, and recreation see heightened activity during the summer months, contributing to upward price pressures.

For example, gasoline prices often rise as people travel more in warmer weather, and demand for fresh produce and other seasonal items can also increase.

(d) **Higher Energy Prices**: The demand for energy, particularly gasoline, tends to rise as temperatures warm up and people engage in more outdoor activities, travel, and vacationing during spring and summer. This increased demand can drive up energy prices, which significantly impact the CPI-U.

(e) **Agricultural and Food Price Changes**: Prices of agricultural products and food items may increase in the first half of the year due to the planting and growing season. Limited supply in early months can lead to price increases until new crops are harvested and brought to market. Transportation costs, weather conditions, and international trade dynamics also play roles in affecting food prices seasonally.

(f) **Economic Growth Factors**: In general, economic activity tends to pick up after the winter months. Increased consumer spending, business investments, and production activities typically result in higher demand for goods and services, leading to price increases.

Employment rates tend to improve in the spring and early summer, leading to higher disposable incomes, which can boost spending further and contribute to inflationary pressures.

(g) **Supply Chain Dynamics**: Seasonal fluctuations in supply chains, such as delays due to weather, increased shipping costs, or supply shortages, can also impact prices in the first half of the year. For instance, disruptions caused by severe winter weather can cause supply chain bottlenecks, leading to a gradual increase in prices as supply catches up with demand from January to July.

(h) **Market Expectations and Speculation**: Traders and businesses may anticipate higher demand in the first half of the year and adjust their pricing strategies accordingly. This expectation-driven price adjustment can contribute to a steady increase in the CPI-U.

3. Comparison Between Years

January to December Comparison: By comparing the values for January 2024 (308.1) and January 2025 (317.5), there is an increase of **9.4 points**, which aligns with the overall trend of rising prices. Similar patterns are seen when comparing other months across the two years, reflecting ongoing inflation.

4. **Possible Economic Implications**

   Inflationary Expectations: The steady increase in the CPI-U suggests inflationary expectations in the U.S. economy. This may affect economic policy, such as interest rates set by the Federal Reserve, wage negotiations, cost-of-living adjustments, and investment strategies.

   Impact on Consumers: Rising CPI-U values indicate that urban consumers can expect higher costs for goods and services over the next two years. This could impact purchasing power, especially for individuals on fixed incomes or those whose wage growth does not keep pace with inflation.

5. **Policy and Planning Considerations**

   Monetary Policy: Policymakers might consider these trends when deciding on measures to control inflation, such as adjusting interest rates or modifying fiscal policies.

   Business Planning: Businesses may use these predictions to plan for potential cost increases in their supply chains, adjust pricing strategies, or manage wage expectations.

Overall, the predicted increase in the CPI-U indicates that consumer prices in the USA are expected to continue rising moderately over the next two years, which could have significant implications for economic policy, business strategy, and household finances.

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