Forecasting Consumer Price Index Trends Using ARIMA models

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Abstract

This analysis forecasts future Consumer Price Index (CPI) values—a critical indicator of inflation—using historical time-series data. The study applies the ARIMA model, recognized for its effectiveness in identifying patterns in economic indicators. Two configurations are utilized: ARIMA (0,2,3) for capturing short-term volatility and ARIMA (2,2,1) for long-term trends. Both configurations were selected through automated processes provided by the pmdarima library. Spanning data from January 1960 to January 2020 for validation, the study demonstrates ARIMA's utility in predicting CPI trends and informing economic policy, particularly during economic disruptions like the COVID-19 recession.

Introduction

Inflation, as measured by the Consumer Price Index (CPI), plays a pivotal role in economic planning and analysis. It reflects changes in the cost of goods and services over time, influencing decisions related to monetary policy, wage adjustments, and purchasing power [1, Dennis 2006 policy]. Policymakers, businesses, and households rely on CPI forecasts to make informed financial decisions. Without effective forecasting, economies risk instability, as unchecked inflation can erode purchasing power and deepen inequality, while deflation suppresses production and employment. Both scenarios are detrimental to the economy and can affect other factors, such as the employment rate or the value of the dollar. To combat rising inflation, the Federal Reserve employs several tools to assess and address its trajectory.

Various forecasting tools have proven instrumental in addressing this need. Forecasting models have been used extensively to analyze and predict the direction of time-series data. The ARIMA model used in this analysis enables the modeling of time-series data by incorporating past data patterns, applying differencing to remove trends, and accounting for random noise. Its parameters—p, d, and q— determine how well the model adapts to specific datasets, making it suitable for complex economic contexts. ARIMA's reliance on time-series data makes it a viable option for utilizing records from the Federal Reserve.

By leveraging ARIMA to forecast U.S. CPI trends, this study demonstrates the model's ability to anticipate inflationary pressures and provide actionable insights for economic stabilization.

International Examples of CPI detriments:

The global significance of accurate inflation forecasting is evident in past economic crises. In Peru during the 1970s, inflation averaged 25% annually, but by the early 1990s, it had spiraled beyond 300%, leading to economic collapse. Reforms such as eliminating wage indexation and adopting a market-driven exchange rate eventually stabilized inflation at under 4% by 1999, but at a steep cost to the nation [6, Mohanty & Klau, 2001].

Conversely, Venezuela's hyperinflation offers a stark reminder of the consequences of inaction. Poor fiscal management and resource misallocation devastated the Bolivar and plunged millions into poverty. Meanwhile, Japan’s struggle with deflation during the 1997–1998 banking crisis highlights the risks of stagnation in a low-price environment [5, Ito & Mishkin, 2004]. These cases underscore the critical need for accurate forecasting tools to prevent economic crises before they escalate. One such tool, renowned for its role in assessing inflation trends, is the Phillips Curve—a cornerstone of macroeconomics [7, bofinger 2024 fighting]. Its development, along with advancements in other forecasting metrics, has significantly simplified the process of evaluating the trajectory of inflation within a country.

Importance of CPI Forecasting

CPI forecasting benefits governments, businesses, and households alike. Policymakers use it to anticipate inflationary or deflationary trends, enabling timely adjustments in interest rates, fiscal measures, and public spending [1, Dennis 2006 policy]. Businesses rely on CPI trends to refine pricing strategies, optimize supply chains, and plan for the long term. Similarly, households benefit from forecasts by using them for budgeting and financial planning. Its value is especially significant when considering the cost of our livelihoods.

Failing to address inflation carries severe consequences. Rising inflation erodes purchasing power and destabilizes financial markets, while prolonged deflation stifles investment and employment. Learning from past mistakes and instances of poor monetary decisions, forecasting models have become essential tools for broader financial institutions, such as the United States Federal Reserve. These models help predict the direction of inflation, enabling policymakers to make informed decisions that benefit the economy. Without such tools, multiple economic catastrophes could arise, further increasing the cost of everyday living. Models like ARIMA allow analysts to identify inflationary pressures early, enabling proactive measures to sustain growth and stabilize economies.

Background of Time-Series Data and ARIMA

Time-series data is a vital resource for professionals across disciplines, including statisticians, economists, and data scientists. Unlike datasets that rely on random sampling, time-series data is sequentially ordered, with observations recorded chronologically. This temporal structure allows analysts to uncover unique features such as serial correlation, trends, seasonality, and patterns, which are essential for understanding and predicting future behavior. By identifying these elements, time-series analysis provides a clearer perspective on underlying dynamics. Techniques like differencing are often applied to remove non-stationarity—unpredictable trends that obscure meaningful patterns—ensuring a stable and reliable analytical foundation.

ARIMA: A Key Model for Time-Series Forecasting

One of the most commonly used methods for time-series forecasting is the AutoRegressive Integrated Moving Average (ARIMA) model, developed by George Box and Gwilym Jenkins. Widely known as the Box-Jenkins model, ARIMA has become a critical tool in economic forecasting, helping businesses analyze financial data and predict stock price movements. Beyond economics, ARIMA has been applied in public health to monitor disease outbreaks and evaluate environmental disturbances, including carbon emissions [3, Kumar, 2010]. Its versatility extends even further, finding applications in crime analytics [3, Islam, 2020] and other fields involving time-series data.

ARIMA consists of three core components:

- AR (AutoRegressive): Captures relationships between a current value and its past observations, represented by the parameter p.

- I (Integrated): Accounts for the degree of differencing (d) required to make the data stationary.

- MA (Moving Average): Reflects how past forecast errors (q) influence current values.

This combination enables ARIMA to model complex time-series data, providing robust insights into future trends.

Modeling

This study utilizes the Auto-Regressive Integrated Moving Average (ARIMA) model to forecast the Consumer Price Index (CPI) based on historical data. Before discussing ARIMA in detail, it is important to understand its simpler predecessor, the Autoregressive Moving Average (ARMA) model, which forms the foundation of ARIMA modeling.

The ARMA Model (p,q)

The ARMA model is designed for stationary time-series data and combines two components: Autoregressive (AR) and Moving Average (MA). Represented as ARMA(p,q) , the structure accounts for dependencies between data points and random errors.

- Autoregressive (AR) Component: The AR component models the current value (xt) as a function of (p) lagged observations:

$$X_t = c + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + w_t$$

- Here, (c) is a constant, (ϕ) are the coefficients of past observations, and (wt) represents white noise.

- Moving Average (MA) Component: The MA component models the current value (xt) as a function of past (q) error terms:

$$X_t = c + w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q}$$

where (θ) are coefficients of past errors.

Combining these two components, the ARMA model effectively predicts stationary series by using past observations and their associated errors to estimate the present value of the data. [4, nyoni2019arima]

The ARIMA Model (p,d,q) Many economic time series, including CPI, are non-stationary, meaning they exhibit trends or seasonality over time. ARIMA extends ARMA by incorporating differencing to make the data stationary. The resulting model is expressed as ARIMA(p,d,q), where:

- (p): The number of lagged observations in the AR component,
- (d): The degree of differencing to achieve stationarity,
- (q): The number of lagged error terms in the MA component.

The integration (I) component, represented by (d), involves transforming the data through differencing:

$$Y_t = x_t - x_{t-1}$$

This process eliminates trends and makes the data suitable for ARMA modeling. The ARIMA model thus accounts for both stationary and non-stationary elements, making it well-suited for economic data analysis.

By combining AR, MA, and differencing components, the ARIMA model is represented mathematically as:

$$X_t = c + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + \theta_1 w_{t-1} + \cdots + \theta_q w_{t-q} + w_t$$

Implementation and Forecasting

This study employs Auto-ARIMA from Python's pmdarima library to identify optimal parameter values for ARIMA. Auto-ARIMA iteratively tests configurations of (p), (d), and (q), selecting the model that minimizes Akaike Information Criterion (AIC) and ensures accuracy while avoiding overfitting. This automated approach expedites the model selection process while maintaining the rigor of traditional Box-Jenkins methodology.

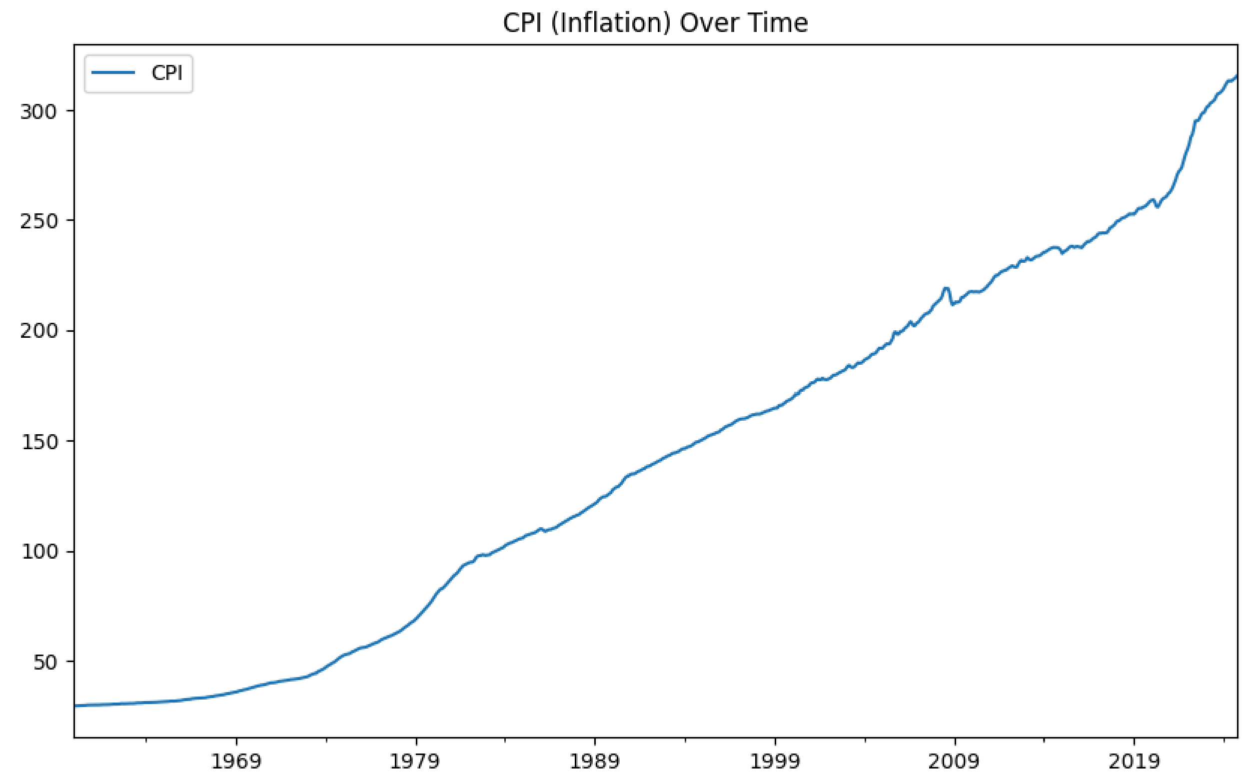
For this analysis:

- ARIMA (0,2,3) is chosen for its robust handling of short-term CPI volatility, as indicated by its lower AIC score.
- ARIMA (2,2,1) is selected for its ability to capture long-term inflation trends, particularly during periods of economic instability like the COVID-19 recession.

The selected models are validated through residual analysis and diagnostic tests, as described in the results section.

Results and Findings of the Data

Time-Series Dataset of CPI from FRED, (01/01/1960-present day):



Summary statistics:

```
Best model:  ARIMA(0,2,3)(0,0,0)[0]
Total fit time: 16.320 seconds
                               SARIMAX Results
==============================================================================
=========
Dep. Variable:                      y   No. Observations:                  778
Model:               SARIMAX(0, 2, 3)   Log Likelihood                -389.153
Date:                Mon, 02 Dec 2024   AIC                            786.305
Time:                        21:39:08   BIC                            804.922
Sample:                    01-01-1960   HQIC                           793.467
                         - 10-01-2024
Covariance Type:                  opg
==============================================================================
=========
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.4157      0.016    -26.147      0.000      -0.447      -0.384
ma.L2         -0.4103      0.019    -21.904      0.000      -0.447      -0.374
ma.L3         -0.0734      0.024     -3.109      0.002      -0.120      -0.027
sigma2         0.1593      0.003     46.580      0.000       0.153       0.166
==============================================================================
==============
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):              4191.34
Prob(Q):                              0.92   Prob(JB):                         0.00
Heteroskedasticity (H):              25.65   Skew:                            -1.05
Prob(H) (two-sided):                  0.00   Kurtosis:                        14.19
==============================================================================
==============
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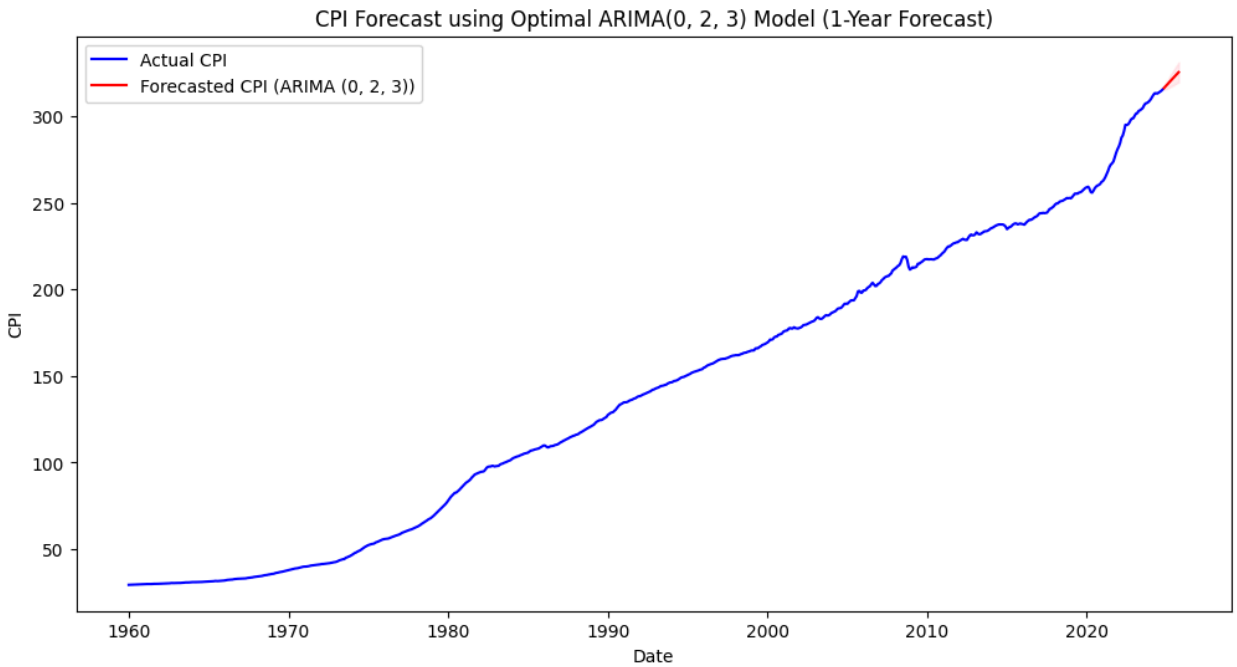
CPI Projection (Base Model, (0,2,3)):



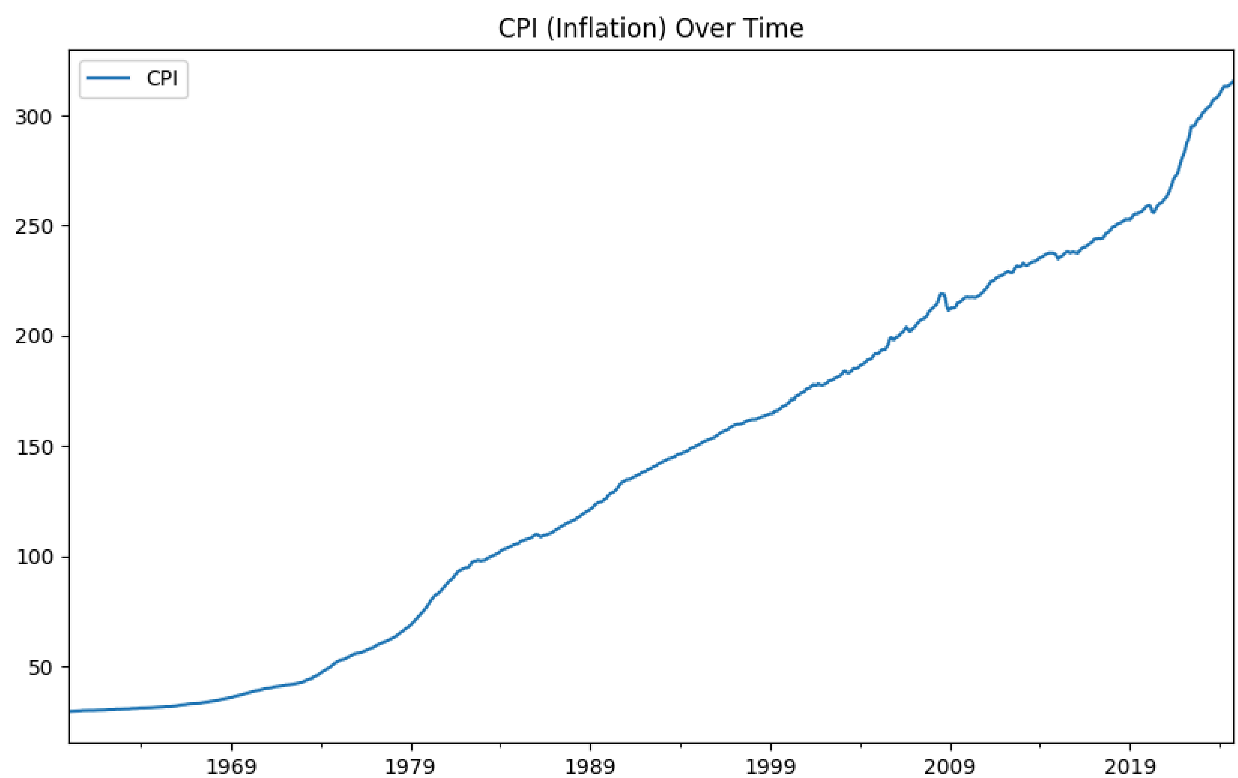
Forecasted CPI Confidence Intervals for the Next Year:

	Forecasted CPI	Lower CI	Upper CI
2024-11-01	316.288057	315.505747	317.070367
2024-12-01	317.116829	315.651141	318.582517
2025-01-01	317.942513	315.932417	319.952609
2025-02-01	318.768197	316.287186	321.249207
2025-03-01	319.593880	316.677478	322.510283
2025-04-01	320.419564	317.087472	323.751657

2025-05-01	321.245248	317.508925	324.981571
2025-06-01	322.070932	317.936976	326.204888
2025-07-01	322.896616	318.368517	327.424715
2025-08-01	323.722300	318.801451	328.643148
2025-09-01	324.547983	319.234304	329.861662
2025-10-01	325.373667	319.666008	331.081326

Backtested Pre-Covid Model:

Data-Set (01/01/1960-01/01/2019):



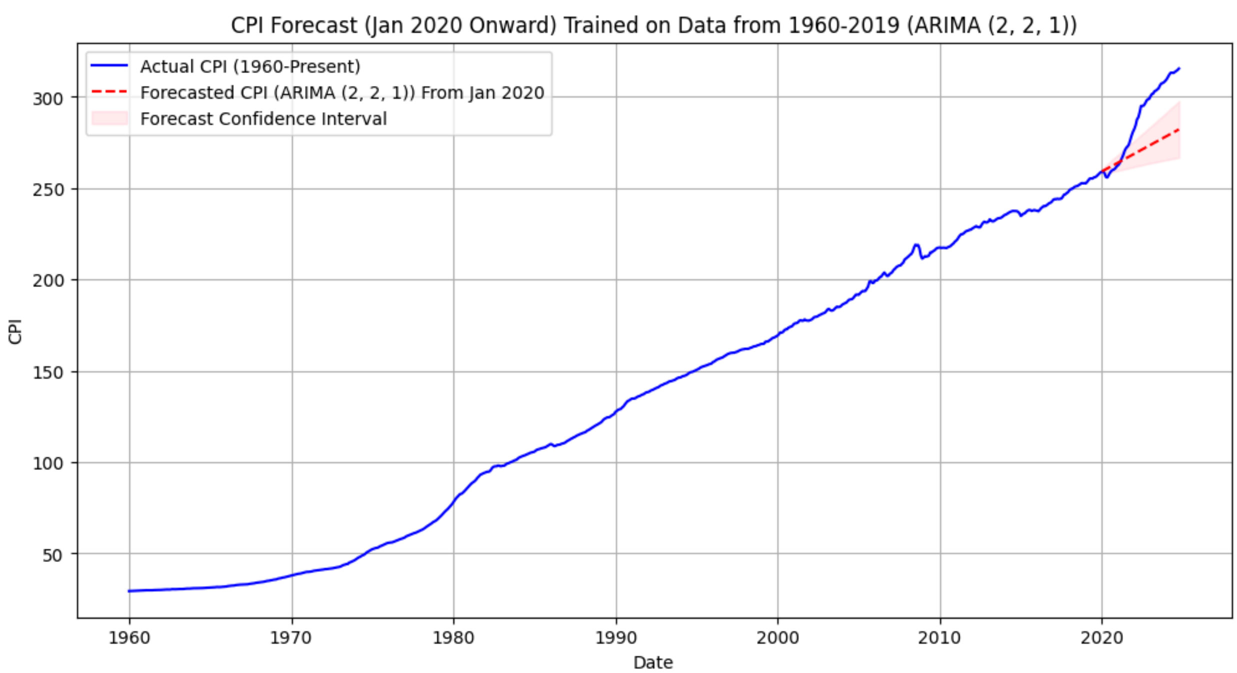
`Pdmarima` (Auto-arima allocation for pre-covid recession) Best Parameter output:

Best model: ARIMA(2,2,1)(0,0,0)[0]

Total fit time: 17.608 seconds

Selected ARIMA Order: (2, 2, 1)

Backtested Forecast (Pre-Covid Recession):



Model Fit

The ARIMA (0,2,3) model demonstrates strong performance, achieving the lowest AIC value (786.305) among tested configurations. This indicates it balances complexity with predictive accuracy effectively for the dataset. The model's BIC score (804.922) and Hannan-Quinn Information Criterion (HQIC, 793.467) further validate its suitability for forecasting CPI.

Significance of Parameters

The summary statistics for the ARIMA (0,2,3) model indicate all coefficients—

(ma.L1), (ma.L2), and (ma.L3)—are statistically significant ((p)-values < 0.05). This demonstrates that the moving average terms significantly enhance the model's forecasting capability. Small standard errors and high z-scores associated with these terms further underline their reliability in capturing patterns within the dataset.

Residual Analysis and Model Diagnostics

- **Ljung-Box Test**: A (p)-value of 0.92 indicates no significant autocorrelation in the residuals, affirming that the model successfully captures the underlying patterns in CPI data. The residuals are uncorrelated and consistent with white noise, validating the model's adequacy.
- **Jarque-Bera Test**: Residual analysis reveals non-normality (($p<0.001$), skewness = -1.05, kurtosis = 14.19). These results suggest external shocks, such as the COVID-19 recession, introduce volatility not fully accounted for by the model.

Non-Normality and External Influences

The heteroskedasticity observed in the residuals (H=25.65) reflects varying CPI volatility across periods. While this does not violate forecasting assumptions, it highlights periods of economic instability, such as the 2008 financial crisis and the COVID-19 recession, where external factors significantly impacted inflation.

Forecasting Accuracy

- **Projection Reliability**: The model forecasts a steady upward trend in CPI, with confidence intervals ranging from 316.29 to 325.57 over one year. While promising, these predictions do not account for external factors like fiscal policy or commodity price shocks, which could affect long-term accuracy.
- **Backtesting Results**: The pre-COVID dataset (1960–2019) produced an ARIMA (2,2,1) model, reflecting stable inflation trends. In contrast, the full dataset (1960–present) exhibits greater volatility, attributed to external shocks such as the pandemic. These results underscore the importance of adaptive modeling in dynamic economic conditions.

Broader Context and Insights

- **Dataset Size**: The extensive dataset (778 observations) provides a comprehensive view of long-term CPI trends but inflates AIC and other criteria. This is expected and does not detract from the model's utility.
- **Economic Implications**: The model's upward CPI forecast highlights persistent inflationary pressures. Policymakers must address these trends proactively, as seen in recent Federal Reserve actions targeting a 2% inflation rate.

Results and Findings of the Data

Model Fit

The ARIMA (0,2,3) model demonstrates strong performance, achieving the lowest AIC value (786.305) among all tested configurations. This indicates a well-balanced trade-off between complexity and predictive accuracy for the dataset. Furthermore, the model's BIC score (804.922) and Hannan-Quinn Information Criterion (HQIC, 793.467) further validate its suitability for forecasting CPI. Due to the size of the model, the forecasting metrics exhibit significantly large values, which can be attributed to the extensive sample size of the time-series data. The recorded instances of multiple volatility patterns and trends in the dataset represent decades of economic occurrences and shocks, spanning from the 1960s to the present day. This demonstrates a significant correlation between forecasting metrics and sample size.

Significance of Parameters

Summary statistics for the ARIMA (0,2,3) model reveal that all coefficients—(ma.L1), (ma.L2), and (ma.L3) —are statistically significant ((p)values<0.05). This confirms the importance of the moving average terms in enhancing the model's forecasting ability. The coefficients' small standard errors and high z-scores underline their reliability in capturing key patterns within the dataset. Patterns such as monetary decisions or policies are captured through the moving averages, which show more complex volatility within the base time series data. This could be from it's capture of the covid-19 recession which significantly spiked our inflation rate, which added more volatility within our time series data.

Residual Analysis and Model Diagnostics

- **Ljung-Box Test:** A (p)-value of 0.92 indicates no significant autocorrelation in the residuals, affirming the model's success in capturing underlying CPI patterns. The residuals are uncorrelated and consistent with white noise, validating the model's adequacy.
- **Jarque-Bera Test:** The residual analysis identifies non-normality ($p<0.001$, skewness = -1.05, kurtosis = 14.19). This suggests that external shocks, such as the COVID-19 recession, introduced volatility not fully accounted for by the model.

Non-Normality and External Influences

Heteroskedasticity in the residuals ($H=25.65$) reflects variations in CPI volatility across different periods. While this does not violate the core forecasting assumptions, it highlights moments of economic instability, such as the 2008 financial crisis and the COVID-19 recession. External factors significantly impact inflation, making it challenging for a univariate model like ARIMA to fully capture these dynamics.

Forecasting Accuracy:

- **Projection Reliability:**

  The ARIMA (0,2,3) model forecasts a steady upward trend in CPI, with confidence intervals ranging from 316.29 to 325.57 over the next year. While the results are promising, external factors such as fiscal policy changes or commodity price shocks are not considered, which could affect the long-term accuracy of these projections.
- **Backtesting Results:**

  When using pre-COVID data (1960–2019), the ARIMA (2,2,1) model demonstrated stable inflation trends and produced significantly lower AIC values compared to the full dataset analysis. This reflects smoother inflationary behavior in the absence of pandemic-driven disruptions. By contrast, the full dataset (1960–present) exhibits greater volatility, attributed primarily to shocks like the COVID-19 recession. These findings are important in regard to adaptive modeling in dynamic economic environments. Further improvement among the backtesting can be done in the form of different statistical approaches or hybrid modeling.

Broader Context and Insights

1. **Dataset Size:**

   The dataset's extensive range (778 observations) provides a comprehensive view of long-term CPI trends. However, it also inflates AIC and other evaluation criteria due to the higher complexity required to model diverse economic periods.

2. **Economic Implications:**

   The model's upward CPI forecast highlights persistent inflationary pressures. This suggests that policymakers must address these trends proactively, as demonstrated by recent Federal Reserve actions targeting a 2% inflation rate. The projected increase in inflation can be mitigated by raising the Federal Funds Rate. This is the Fed's primary tool for managing rapidly rising inflation. By increasing interest rates, the Fed can slow the rate of growth in the CPI, thereby stabilizing the economy.

Conclusion

This study demonstrates the effectiveness of ARIMA modeling for forecasting CPI trends using historical data. The ARIMA (0,2,3) configuration successfully captures short-term inflation volatility, while the ARIMA (2,2,1) model provides valuable insights into longer-term economic trends. These models prove particularly useful during periods of relative stability, but external shocks—such as the COVID-19 recession—pose significant challenges.

Despite its strengths, the analysis reveals some limitations of ARIMA modeling. External shocks, such as economic recessions or unexpected Federal Reserve policy shifts, introduce volatility that the model cannot fully account for. The observed non-normality in residuals, as indicated by the Jarque-Bera test, further emphasizes the presence of outliers or structural breaks in the data. Additionally, the heteroskedasticity observed in the residuals highlights the need for models that can dynamically adapt to varying levels of volatility.

Limitations and Potential Improvements

1. **Univariate Focus:**

   ARIMA models rely solely on a single dependent variable, as was the case in this analysis. This univariate approach omits critical factors such as interest rates, commodity prices, and fiscal policies, potentially leading to omitted variable bias. Incorporating these variables through a multivariate approach—such as Vector Autoregression (VAR)—could significantly enhance explanatory power and provide a more comprehensive analysis of inflationary trends.

2. **Non-Normal Residuals and Long-Term Predictions:**

   The non-normality in residuals suggests that the model does not fully capture all underlying patterns, an issue compounded by its univariate nature. Employing an ARIMA-GARCH model could address heteroskedasticity by accounting for variations in residual variance over time.

   Regarding long-term predictions, the reliance on historical data limits accuracy.

Exploring ensemble methods or incorporating stochastic trend components could improve model robustness and better account for long-term economic shifts.

Final Thoughts

The ARIMA model provides valuable insights into CPI trends and proves to be a useful tool for economic forecasting and decision-making. However, addressing its limitations—particularly in handling external shocks and incorporating multivariate dynamics—could refine its application, especially in rapidly changing environments.

Future work should explore hybrid forecasting models and multivariate approaches, such as VAR, to enhance model robustness and adaptability. Unlike ARIMA, which focuses on patterns within CPI data, VAR considers interdependencies between multiple variables, such as CPI and interest rates, potentially creating more accurate models.

While this study serves as a foundational analysis, it also highlights areas for improvement and further research. The findings demonstrate the potential of using ARIMA for inflation trajectory analysis, offering a practical starting point for future advancements in economic forecasting.

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