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Dynamics and Short-Term Forecasting of the U.S. Consumer Price Index: An Empirical Analysis

Abstract
This article presents an empirical analysis of the dynamics and short-term forecasting of the U.S. Consumer Price Index (CPI) using econometric time-series modeling techniques. Official macroeconomic data from the Federal Reserve Bank of St. Louis (FRED) serve as the empirical basis for the study. Preliminary analysis reveals the non-stationary nature of the original time series, which necessitates the application of ARIMA-class models incorporating differencing. The optimal model specification is selected based on the Akaike and Bayesian information criteria, while model adequacy is confirmed through residual diagnostics. Based on the selected specification, short-term forecasts are generated over a 12-period horizon with corresponding confidence intervals. The forecasting results indicate the persistence of a moderately upward trend in the Consumer Price Index over the projected period. Forecast accuracy is further assessed using the Mincer–Zarnowitz test, which detects no statistically significant bias and confirms both the unbiasedness and informational efficiency of the forecasts. Overall, the findings demonstrate the high predictive performance of ARIMA models in analyzing CPI dynamics and their practical relevance for assessing short-term monetary conditions.
Keywords: consumer price index; time series; ARIMA; short-term forecasting; U.S. economy.

Introduction
Consumer Price Indices (CPI) constitute a key macroeconomic indicator reflecting the dynamics of inflationary processes and forming the basis for decision-making in monetary policy, macroeconomic forecasting, and the assessment of real economic conditions. For the U.S. economy, which plays a systemic role at the global level, CPI behavior is of particular analytical and practical importance, as inflationary trends directly affect interest rates, financial markets, and international capital flows (Stock & Watson, 2019; Faust & Wright, 2013).
In an environment of heightened macroeconomic uncertainty amplified by structural shifts, changes in

monetary policy regimes, and external shocks the demand for reliable short-term inflation forecasting tools has increased substantially. Accurate assessments of CPI dynamics are essential not only for monitoring inflation risks but also for analyzing real interest rates and evaluating current monetary conditions. Recent studies emphasize that, at short forecasting horizons, inflation processes exhibit pronounced inertia, which makes statistical time-series models especially relevant (Faust & Wright, 2013; Argiri et al., 2024).

Despite the rapid development of structural models and machine learning methods, the empirical literature demonstrates that simple univariate models often remain highly competitive benchmarks. Stock and Watson (2019) show that even extended inflation models frequently fail to outperform forecasts generated by autoregressive and ARIMA-based approaches, particularly in pseudo out-of-sample evaluations. Other studies confirm that the relative advantages of alternative models depend on the inflation regime and forecasting horizon, while their predictive performance may vary significantly over time (Dotsey et al., 2018).

A separate strand of the literature examines the role of structural factors and the Phillips curve in inflation forecasting. The results point to the conditional nature of their predictive usefulness: the relationship between inflation and real economic activity may weaken or strengthen depending on the macroeconomic regime and the stage of the business cycle (Dotsey et al., 2018). In parallel, a growing body of research focuses on real-time forecasting and nowcasting of CPI using high-frequency price data and machine learning techniques, which demonstrate potential gains in short-term accuracy but also underscore the necessity of benchmarking against strong statistical models (Beck et al., 2023; Barkan et al., 2023). An essential component of empirical forecasting analysis is the evaluation of forecast quality. In applied macroeconomics, the Mincer–Zarnowitz test remains a standard tool for assessing the unbiasedness and informational efficiency of forecasts (Hendry & Clements, 2001). Recent studies on central bank inflation forecasts indicate that even when average forecast errors are acceptable, forecasts may exhibit bias or efficiency losses over specific periods, making formal verification of their statistical properties critically important (Argiri et al., 2024).

The objective of this study is to conduct an empirical analysis of the dynamics of the U.S. Consumer Price Index and to construct short-term forecasts using ARIMA-class models based on official macroeconomic data from the Federal Reserve Bank of St. Louis (FRED). The analysis includes stationarity testing of the time series, selection of the optimal model specification using the Akaike and Bayesian information criteria, and comprehensive residual diagnostics. Forecasts are generated over a 12-period horizon and complemented with confidence intervals, while their quality is evaluated using the Mincer–Zarnowitz test.

The scientific novelty of the study lies in the systematic application of classical econometric techniques to short-term CPI forecasting with an explicit emphasis on the statistical validation of forecasts. The practical significance of the research is determined by the applicability of the results to analytical work, macroeconomic monitoring, and the assessment of short-term monetary conditions.

Literature review

The task of forecasting inflation, and CPI dynamics in particular, is among the most extensively studied problems in applied macroeconometrics. Nevertheless, a broad consensus in the literature holds that simple statistical benchmarks often remain highly competitive (Barkan et al., 2023). In their seminal contribution, Stock and Watson (2019) demonstrate that Phillips curve–based models and specifications incorporating alternative macroeconomic predictors frequently yield only limited accuracy gains relative to simple time-series models at a 12-month horizon, especially in pseudo out-of-sample comparisons.

More recent surveys emphasize that robust improvements in forecasting performance are typically achieved either through combinations of models and expert expectations or through carefully selected benchmarks and explicit consideration of regime changes in inflation dynamics. A key implication of this strand of research is that univariate models from the AR/ARIMA class often serve as a benchmark that is difficult to systematically outperform, thereby justifying their use in short-term CPI forecasting as a transparent and reproducible tool.

A separate branch of the literature investigates the conditions under which structural Phillips curve–based models improve inflation forecasts. The evidence suggests that their predictive usefulness is conditional: the contribution of real activity and economic slack to inflation forecasting varies over time and may depend on the prevailing regime (e.g., stable inflation versus post-shock periods). In parallel, a growing literature on nowcasting and real-time inflation forecasting employs high-frequency price data and machine learning techniques to produce timely CPI estimates prior to the release of official statistics. While these approaches demonstrate potential improvements in short-term accuracy under conditions of heightened volatility, they also underscore the importance of benchmarking against strong statistical baselines. Within this framework, ARIMA models remain a rational baseline choice, as they provide an interpretable representation of inflation dynamics and allow for a robust construction of confidence intervals when appropriately specified and diagnosed.

A rigorous evaluation of forecast quality constitutes a central standard in empirical macroeconomics. The traditional approach relies on regression-based tests of forecast unbiasedness and informational efficiency, most notably the Mincer–Zarnowitz test. Contemporary applied studies of central bank inflation forecasts similarly focus on bias and efficiency properties at short horizons, showing that even when average forecast accuracy is satisfactory, forecast quality may deteriorate as the horizon increases. In the present study, these evaluation techniques are employed to provide a comprehensive verification of short-term CPI forecasts based on official FRED data, thereby ensuring reproducibility and comparability with established macroeconomic monitoring practices.

Methodologically, macroeconomic time-series analysis faces the fundamental challenge of non-stationarity. The classic result of Nelson and Plosser shows that many U.S. macroeconomic indicators can be characterized as unit-root processes, implying the presence of stochastic trends and the necessity of properly accounting for integration in modeling and forecasting (Nelson & Plosser, 1982). A key practical implication of this literature is that unit-root testing must precede ARIMA estimation, and differencing should be applied when necessary; otherwise, the parameters of the autoregressive component may fall outside the stationarity region, rendering statistical inference invalid (Garcia et al., 2023).

In applied econometrics, unit-root tests from the Dickey–Fuller family represent the standard approach to assessing stationarity. Dickey and Fuller (1979) formalize the asymptotic properties of estimators and test statistics in the presence of a unit root, providing the foundation for subsequent developments. The augmented Dickey–Fuller (ADF) test extends this framework to account for more complex error dynamics; in particular, Said and Dickey (1984) justify approximating ARMA processes with higher-order autoregressions when the underlying lag structure is unknown. For short-term CPI forecasting, this literature establishes a clear empirical workflow: (i) testing for integration, (ii) transforming the series to stationarity if required, (iii) model estimation, and (iv) post-estimation diagnostic checking.

Forecasting within the ARIMA framework traditionally relies on systematic identification and diagnostic procedures, with particular emphasis on residual analysis and the absence of serial correlation, i.e., the white-noise condition (Hassani et al., 2025). The most widely used statistical tool in this context is the Ljung–Box test, a modification of the general Q-statistic that provides improved distributional approximations and more reliable inference regarding misspecification in ARMA/ARIMA models (Ljung & Box, 1978). In empirical applications, this allows researchers to formally verify that the model has adequately captured the systematic component of the dynamics and that the residuals do not contain predictable structure.

An important practical step in applied forecasting is the selection of model parameters and comparison criteria across alternative specifications. Automatic ARIMA selection based on information criteria (AIC, AICc, BIC) and stepwise search procedures is widely used (Escudero et al., 2021). A canonical reference in this area is Hyndman and Khandakar (2008), who describe automated forecasting algorithms for large collections of univariate time series and discuss practical aspects of estimation and model selection in the R environment. This approach is methodologically well-suited to macroeconomic data, where manual identification may be sensitive to sample choice, shock structures, and data revisions.

Finally, the applied relevance of statistical forecasting models is supported by large-scale comparative studies of forecast accuracy. The findings of the M3-Competition indicate that relatively “simple” statistical methods, including time-series models, often achieve competitive accuracy, particularly at short horizons. This evidence further supports the use of ARIMA models as a justified baseline tool for practical forecasting of economic indicators (Makridakis & Hibon, 2000).

According to data from the Federal Reserve and the ECB, following the global financial crisis the effective real interest rate (ERIR) in advanced economies remained structurally low, reinforcing the hypothesis that long-run forces related to capital accumulation, demographics, and innovation diffusion dominate its behavior (Del Negro et al., 2019; Rachel & Summers, 2019). Del Negro et al. (2019) document that the decline in ERIR is internationally synchronized, while Rachel and Summers (2019) link this phenomenon to secular stagnation. In the post-pandemic period, renewed debate has emerged regarding a potential increase in ERIR driven by inflationary shocks and accelerated investment in decarbonization, infrastructure, and digitalization (Holston et al., 2023; Jordà & Nechio, 2023). Nevertheless, assessments by the Federal Reserve Bank of New York and the ECB suggest that the structural drivers of low ERIR remain in place, making a return to 1990s levels unlikely (Wellink, 2023).

Materials and methods

The empirical analysis is based on official macroeconomic data obtained from the Federal Reserve Bank of St. Louis database (FRED, 2026). The primary object of analysis is the Consumer Price Index (CPI), which represents a time series reflecting the dynamics of inflationary processes in the U.S. economy. The choice of the sample period is determined by data availability and ensures a sufficient sample length for reliable econometric modeling and forecasting.

At the first stage, a preliminary analysis of CPI dynamics is conducted, including graphical visualization and formal testing of its stochastic properties. The analysis indicates that the original time series exhibits pronounced non-stationarity, which is a characteristic feature of macroeconomic price indicators. To formally assess the presence of a unit root, standard stationarity tests are applied. The results indicate that the CPI series is integrated of order one, which necessitates first differencing to transform the series into a stationary form.

Given the non-stationary nature of the original series, subsequent analysis is carried out using ARIMA (p, d, q) models, with the order of differencing d fixed at one. Various combinations of the autoregressive (p) and moving average (q) orders are considered to determine the optimal model structure.

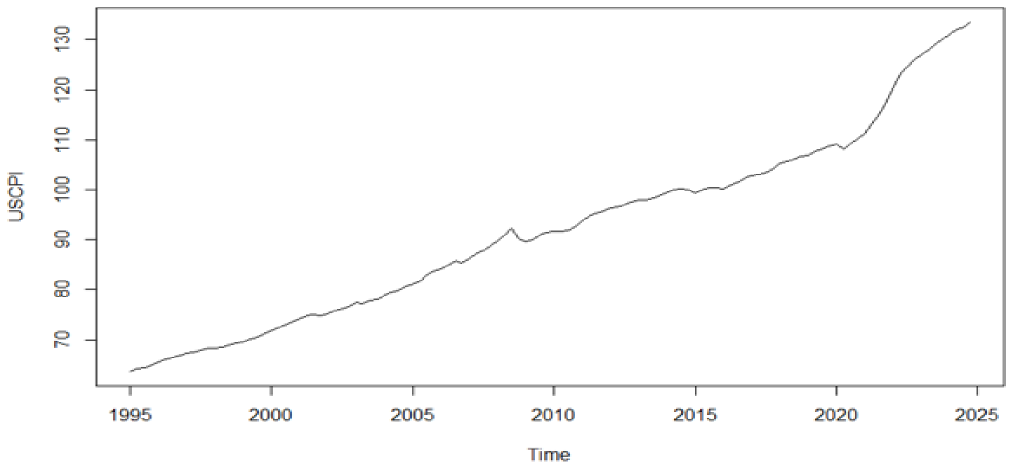
The selection of the optimal model specification is based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The final model is chosen as a compromise solution that minimizes these criteria while maintaining the statistical significance of the estimated parameters and the overall econometric consistency of the specification. To assess the adequacy of the selected ARIMA model, a comprehensive residual diagnostics procedure is conducted. The residuals are examined for the presence of autocorrelation, deviations from normality, and heteroskedasticity. The absence of statistically significant autocorrelation and the stability of residual variance confirm the correctness of the model specification and its suitability for subsequent forecasting. Based on the selected ARIMA model, short-term forecasts of the U.S. Consumer Price Index are generated over a 12-period horizon. In addition to point forecasts, confidence intervals are constructed to reflect forecast uncertainty and to allow for a probabilistic interpretation of expected CPI dynamics in the short run.

The quality of the resulting forecasts is evaluated using the Mincer–Zarnowitz test, which is applied to assess the unbiasedness and informational efficiency of the forecast estimates. Within this framework, the presence of systematic forecast bias and the ability of forecasts to adequately reflect available information are examined. The test results indicate no statistically significant bias and confirm the high quality of the short-term forecasts obtained from the ARIMA model.

Results

The analysis of the dynamics of the original data constitutes a necessary stage of the empirical investigation, as it allows for the identification of general trends in the time series and the formulation of preliminary hypotheses regarding its statistical properties. Figure 1 illustrates the dynamics of the U.S. Consumer Price Index (CPI) over the period 1995–2025, which is subsequently used to compute the real interest rate. The CPI serves as a deflator that adjusts the nominal interest rate for the inflation component, which is critically important for determining its real level (figure 1).

Figure 1. US CPI dynamics from 1995 to 2025.



As can be seen from the graph, the time series is characterized by a pronounced upward trend throughout the entire observation period. In the first half of the sample (1995–2008), the growth of the U.S. CPI was relatively smooth, reflecting moderate inflationary pressures and a stable macroeconomic environment. Following the 2008 financial crisis, a short-term deceleration is observed; however, from 2010 onward, growth resumes and remains persistent.

The most significant changes occur in the post-2020 period, when the rate of increase in the U.S. CPI accelerates markedly. This surge is associated with a combination of factors, including pandemic-related shocks, disruptions in global supply chains, the expansion of fiscal stimulus measures, and shifts in monetary policy. As a result, by 2025 the index reaches historically high levels, indicating a substantial intensification of inflationary processes in the U.S. economy.

The graphical behavior of the series suggests non-stationarity, the presence of a deterministic trend component, and the potential necessity of differencing when constructing econometric models. Based on this preliminary analysis, subsequent sections focus on modeling the real interest rate using time-series methods and generating short-term forecasts.

The stationarity of the series is formally examined using the Augmented Dickey–Fuller (ADF) test (table 1).

Table 1. Augmented Dickey-Fuller (ADF) Test

Data	**USCPI**
Dickey-Fuller	-0.53715
Lag order	4
p-value	0.9788
alternative hypothesis	stationary

The results of the Augmented Dickey–Fuller (ADF) test indicate no statistical grounds for rejecting the null hypothesis of a unit root (p-value=0.9788), confirming the non-stationarity of the original U.S. CPI series. Consequently, transformation of the series through differencing is required to achieve stationarity prior to further modeling.

After differencing the U.S. CPI time series, four econometric models are estimated.

Table 2. Model 1-4 Arima

	Model 1 Arima (1,1,1)	**Model 2 Arima (2,1,0)**	**Model 3 Arima (0,1,1)**	**Model 4 Arima (2,1,2)**
ar1	0.9398	0.5815	-	0.4195
s.e.	0.0408	0.0892	-	0.2268
ar2	-	0.2225	-	0.5216
s.e.	-	0.0893	-	0.2007
ma1	-0.5209	-	0.6325	0.0833
s.e.	0.1225	-	0.0654	0.2271
ma2	-	-	-	-0.4936
s.e.	-	-	-	0.1124
sigma^2	0.2838	0.2989	0.4301	0.2761
log likelihood	-93.46	-96.44	-118.39	-90.9
AIC	192.92	198.88	240.79	191.8
BIC	201.25	207.22	246.35	205.7

We proceed by comparing the models in order to identify the specification with the highest forecasting performance. Within the empirical analysis, several alternative time-series model specifications for the U.S. CPI are estimated. Model selection is based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which allow for the comparison of competing models while accounting for both goodness of fit and model complexity (Table 3).

Table 3. Comparison of models using penalty criteria

	Model	AIC	BIC
1	ARIMA (1,1,1)	192.9158	201.2532
2	ARIMA (2,1,0)	198.8790	207.2163
3	ARIMA (0,1,1)	240.7880	246.3463
4	Auto	191.8009	205.6965

Table 3 reports the AIC and BIC values for the following specifications: the automatic model selected by the *auto.arima* algorithm, as well as the ARIMA (1,1,1), ARIMA (2,1,0), and ARIMA (0,1,1) models. The lowest values of both information criteria are obtained for the automatically selected model (AIC = 191.8009; BIC = 205.6965), indicating the most favorable balance between goodness of fit and the number of estimated parameters.

Among the manually specified models, ARIMA (1,1,1) exhibits the lowest AIC and BIC values (AIC = 192.9158; BIC = 201.2532), although its performance is slightly inferior to that of the automatic specification. The ARIMA (2,1,0) model is associated with higher information criterion values, suggesting weaker performance relative to the preceding models. The least preferred specification is ARIMA (0,1,1), which yields substantially higher AIC and BIC values, indicating inadequate representation of the time-series dynamics.

To assess the presence of autocorrelation in the residuals of the selected ARIMA (2,1,2) model, the Ljung–Box test is applied, which is a standard diagnostic tool for evaluating the adequacy of time-series models.

Table 4. Ljung-Box test

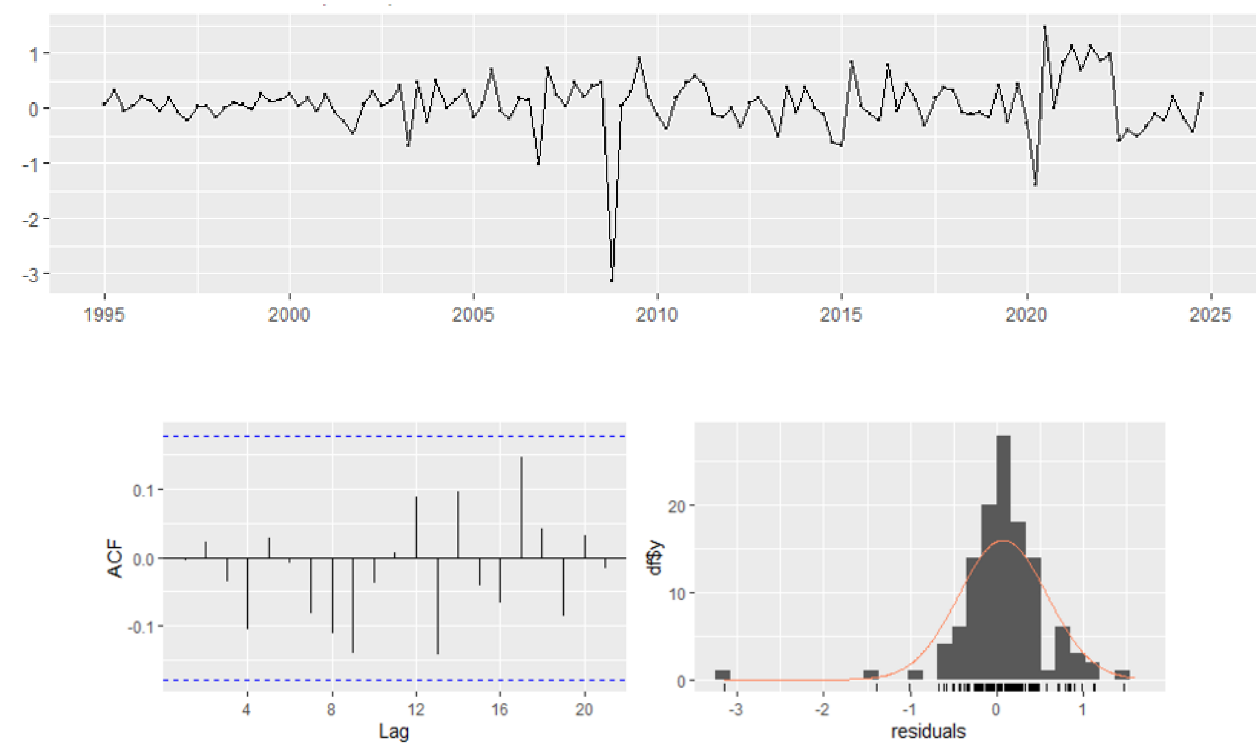
data	Residuals from ARIMA (2,1,2)
Q*	4.1947
df	4
p-value	0.3803
Model df	4
Total lags used	8

The test results indicate that the Ljung–Box statistic equals $Q^* = 4.1947$ with $df = 4$ degrees of freedom and a corresponding p-value $= 0.3803$. The obtained p-value substantially exceeds conventional significance levels (0.10, 0.05, and 0.01), implying that there is no statistical evidence to reject the null hypothesis of no residual autocorrelation.

Accordingly, it can be concluded that the residuals do not exhibit statistically significant autocorrelation and possess the properties of white noise. This finding indicates a correct specification of the ARIMA (2,1,2) model and confirms that it effectively captures the temporal dependence present in the original series. The results of the Ljung–Box test therefore support the suitability of the selected model for further analysis and short-term forecasting of the Consumer Price Index.

To further assess the adequacy of the ARIMA (2,1,2) model, a residual diagnostics analysis is conducted, including visual inspection of residual dynamics over time, examination of the autocorrelation function, and evaluation of the residual distribution (Figure 2).

Figure 2. Residual diagnostics of the ARIMA (2,1,2) model.



The time-series plot of the residuals (Figure 2) shows no pronounced trend or systematic pattern, indicating that the model satisfactorily captures the main dynamics of the original series. The residuals fluctuate around a zero mean, which suggests a correct specification of the conditional mean component of the model. At the same time, short-lived outliers are observed in certain subperiods, most notably during episodes of heightened macroeconomic turbulence. These deviations may reflect the influence of exogenous shocks that are not fully captured by the model.

The autocorrelation function (ACF) of the residuals indicates that the majority of autocorrelation coefficients lie within the 95% confidence bounds, supporting the conclusion that no statistically significant residual autocorrelation is present. This result implies that the model effectively removes linear dependence in the time series and satisfies the assumption of uncorrelated errors.

The residual histogram exhibits a distribution close to normal, with a concentration of observations around zero. Minor departures from normality and the presence of a limited number of extreme observations are consistent with the nature of macroeconomic data and do not materially affect the quality of parameter estimation or forecasting performance.

We now turn to short-term forecasting based on the selected model (Table 5). Using the optimal time-series specification, a short-term forecast of the indicator is generated over a 12-period (quarterly) horizon.

Table 5. Short-term forecasting results for the next 12 quarters.

Period	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2025 Q1	134.4365	133.7631	135.1100	133.4066	135.4665
2025 Q2	135.1917	133.9761	136.4073	133.3326	137.0508
2025 Q3	135.9704	134.2811	137.6596	133.3869	138.5538
2025 Q4	136.6909	134.4860	138.8958	133.3188	140.0630
2026 Q1	137.3993	134.6731	140.1255	133.2299	141.5687
2026 Q2	138.0723	134.8005	141.3441	133.0686	143.0761
2026 Q3	138.7241	134.8935	142.5548	132.8657	144.5826
2026 Q4	139.3486	134.9429	143.7544	132.6106	146.0866
2027 Q1	139.9506	134.9576	144.9436	132.3145	147.5867
2027 Q2	140.5288	134.9369	146.1208	131.9767	149.0810
2027 Q3	141.0854	134.8849	147.2859	131.6026	150.5682
2027 Q4	141.6205	134.8030	148.4380	131.1940	152.0470

Table 5 reports the point forecasts along with the corresponding 80% and 95% confidence intervals, which makes it possible to assess not only the expected trajectory of the indicator but also the degree of forecast uncertainty.

The point forecasts exhibit a moderately upward trajectory over the entire forecasting horizon. According to the results, the forecasted values increase steadily from early 2025 through the end of 2027, indicating the persistence of a gradual upward trend in the Consumer Price Index in the short run.

The confidence intervals widen as the forecasting horizon increases, which is a typical feature of time-series models and reflects the accumulation of uncertainty over time. Nevertheless, even at the maximum forecast horizon, the intervals remain relatively narrow, suggesting stability of the model estimates and an acceptable level of forecast accuracy. The 80% confidence intervals are substantially narrower than the 95% intervals, further illustrating the range of plausible scenarios for the evolution of the indicator under different probability assumptions.

To evaluate the quality of the forecasts generated by the ARIMA(2,1,2) model (fit_best), the Mincer–Zarnowitz test is applied. This test is based on a regression of the realized values of the indicator on the corresponding forecast values and allows for an assessment of forecast unbiasedness and informational efficiency. The regression model is specified as follows:

$$y_t = \alpha + \beta \hat{y}_t + \varepsilon_t, \qquad (1)$$

where $y_t$denotes the actual value of the indicator, $\hat{y}_t$represents the forecasted value, and $\alpha$and $\beta$are parameters to be estimated.

An ideal forecast—one that is both unbiased and informationally efficient—corresponds to the fulfillment of the following null hypothesis:

$$H_0\colon \alpha = 0, \beta = 1. \qquad (2)$$

The evaluation of forecast quality involves testing the following hypotheses:

(1) Test of the hypothesis

$$H_0: \beta = 1 \qquad (3)$$

The results of the linear hypothesis test yield an F-statistic of 1.855 with a corresponding, p-value = 0.187.

Since the p-valueexceeds conventional significance levels (0.10, 0.05, and 0.01), there is no statistical basis for rejecting the null hypothesis that the coefficient on the forecast equals unity. This result indicates that the forecasts do not exhibit systematic scale bias and adequately capture the amplitude of fluctuations in the realized series.

(2) Joint test of the hypotheses $H_0: \alpha = 0$ и $\beta = 1$

The results of the joint test yield an F-statistic of 1.5415 with a corresponding, p-value = 0.2363.

The obtained p-valuealso substantially exceeds conventional significance levels, implying that the joint null hypothesis cannot be rejected. Consequently, the model's forecasts can be regarded as unbiased and statistically consistent with the observed data.

To enhance the robustness of the conclusions, coefficient estimates are additionally obtained using Newey–West robust standard errors, which are consistent in the presence of heteroskedasticity and weak autocorrelation. The results indicate that the coefficient on the forecasted value is highly statistically significant, with $\hat{\beta} = 0.9807(p < 0.001)$, confirming the strong explanatory power of the forecast component. The intercept term is statistically insignificant (p-value $= 0.1234$), which further supports the absence of systematic forecast bias. Importantly, these conclusions remain robust when the robust covariance matrix is employed.

To assess out-of-sample forecasting accuracy, additional forecast performance measures are reported in Table 6:

Table 6. Model quality diagnostics

Indicators	Value in percent
RMSE	0.6857
MAE	0.5522
MAPE	0.474

Low error values, particularly a MAPE below 1%, indicate high short-term forecasting accuracy and confirm the practical applicability of the model.

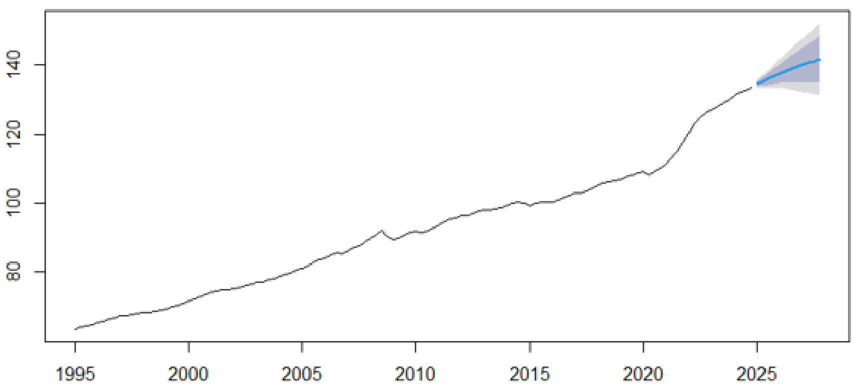


Figure 3. Forecast dynamics based on the selected ARIMA model.

Figure 3 presents the forecast of the analyzed indicator generated using the optimally selected ARIMA model. As shown, the observed time series exhibits a persistent upward trend over the period 1995–2024, with the most pronounced increase occurring during the post-pandemic period of 2020–2023. This pattern indicates strong inertia and a gradual upward shift in the level of the indicator over time.

Discussion

Based on the minimum values of the Akaike and Bayesian information criteria, the model selected by the *auto.arima* algorithm is identified as the optimal specification for subsequent analysis and forecasting of Consumer Price Index dynamics. This result confirms the appropriateness of automated model selection procedures when modeling non-stationary macroeconomic time series.

Diagnostic results confirm the adequacy of the ARIMA (2,1,2) model: the residuals can be treated as approximately white noise, exhibiting neither pronounced autocorrelation nor systematic patterns. This finding indicates correct model specification and supports its suitability for short-term forecasting of the U.S. Consumer Price Index. The obtained forecasts suggest the persistence of relatively tight monetary conditions in the short run. The projected increase in the Consumer Price Index may exert a restraining effect on investment and consumer activity, while simultaneously supporting financial stability through higher real returns on savings. Overall, the forecasting results confirm the applicability of the selected model for short-term analysis of CPI dynamics. The combination of point forecasts and confidence intervals allows the estimates to be effectively used in analytical and applied studies related to the assessment of monetary conditions and macroeconomic expectations.

The results of the Mincer–Zarnowitz test reveal no statistically significant forecast bias for the ARIMA(2,1,2) model. The null hypothesis of forecast unbiasedness and informational efficiency $(\alpha = 0, \beta = 1)$ cannot be rejected under both standard estimation and when using Newey–West robust standard errors. This provides strong evidence of the model's high predictive performance and supports its use for short-term forecasting of U.S. CPI dynamics.

The constructed forecast indicates the continuation of a moderately upward trajectory over the short-term horizon through 2027, consistent with the historical patterns identified in the data. The forecast confidence intervals are symmetric around the point forecast and widen as the forecast horizon increases, reflecting growing uncertainty at longer horizons—a typical characteristic of ARIMA models. The relatively narrow confidence intervals at the beginning of the forecast horizon indicate strong predictive ability and satisfactory stability of the model estimates. Taken together, the results confirm the adequacy of the selected ARIMA model and its suitability for short-term forecasting of the analyzed indicator.

Conclusion

Within this study, an empirical assessment of the dynamics and short-term forecasting of the U.S. Consumer Price Index was conducted using time-series analysis techniques. The main findings can be summarized as follows.

(1) Analysis of the original time series reveals pronounced non-stationarity, as confirmed by the

Augmented Dickey–Fuller test. This result justifies the use of differencing and the application of ARIMA-class models, which are appropriate for modeling integrated macroeconomic indicators.

(2) Based on a comparison of alternative specifications using the Akaike and Bayesian information criteria, an optimal ARIMA model is selected that provides the best balance between goodness of fit and model parsimony. Residual diagnostics indicate the absence of statistically significant autocorrelation and systematic patterns, confirming correct model specification and the validity of the white-noise error assumption.

(3) Short-term forecasting over a 12-period horizon reveals a moderately upward trajectory of the Consumer Price Index in the forecast interval. The 80% and 95% confidence intervals exhibit an acceptable degree of uncertainty and confirm the stability of the forecast estimates, even as the forecast horizon increases.

(4) Forecast quality is further evaluated using the Mincer–Zarnowitz test. The results of both individual and joint hypothesis tests reveal no statistically significant forecast bias: the null hypothesis that the intercept equals zero and the slope coefficient equals unity cannot be rejected. This finding indicates that the forecasts are unbiased and informationally efficient.

(5) Out-of-sample forecast accuracy measures (RMSE, MAE, and MAPE) display low error levels, confirming the high short-term predictive performance of the model and its practical applicability for analytical purposes.

Overall, the results demonstrate that ARIMA models, when combined with proper stationarity testing and residual diagnostics, constitute an effective tool for short-term forecasting of the U.S. Consumer Price Index. The obtained estimates can be applied in applied macroeconomic and financial research for assessing monetary conditions and constructing forecast scenarios, and they may also serve as a foundation for future extensions incorporating exogenous variables and alternative forecasting methods.

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