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Analysis and Forecasting of the Consumer Price Index (CPI) in Türkiye Using ARFIMA and GARCH Models

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Abstract
This study examines the dynamic behavior of Turkey's Consumer Price Index (CPI) over the period under consideration and provides short-term forecasts for the year 2026 by employing an ARFIMA(2,d,2)–GARCH(1,1) modeling framework. The estimation results reveal that all parameters in both the mean and variance equations are statistically significant, indicating a strong autoregressive structure, notable short-term error dynamics, and pronounced long-memory characteristics in the CPI series. The GARCH component suggests a highly persistent volatility process, with α(1) + β(1) approaching unity, implying that inflation shocks exhibit long-lasting effects. Forecasts for 2026 show a steadily increasing CPI throughout the year, rising from 3457.25 in January to 4495.01 in December, corresponding to an approximate annual increase of 30 percent. These findings indicate that inflationary pressures remain robust and persistent, driven by structural and long-memory dynamics embedded in the series. The study highlights the challenges of achieving rapid disinflation and underscores the need for sustained and credible policy interventions to ensure price stability.
Keywords: *CPI, Inflation Forecasting, ARFIMA, Time Series*

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I. Introduction

The ARFIMA (p, d, q) model is classified as a long-memory time series model. Unlike conventional ARIMA models, ARFIMA incorporates not only autoregressive and moving average components but also a fractional integration parameter, denoted by d. This feature enhances the model's flexibility and allows for a more accurate representation of long-term dependence in time series data. Consequently, ARFIMA models are widely used to capture and forecast the long-run dynamics of economic and financial time series (Kutlar & Turgut, 2006).

In the estimation of ARFIMA models, three primary methods are commonly employed in the literature: the Exact Maximum Likelihood Estimation, the Modified Profile Likelihood Estimation, and the Nonlinear Least Squares Estimation methods (Doornik & Ooms, 2004). These approaches are particularly important for obtaining consistent and efficient estimates of the long-memory parameter.

The Consumer Price Index (CPI) is a key indicator that measures changes in the prices of goods and services consumed by households over time. In Türkiye, the CPI has been constructed with 2003 as the base year, and its primary objective is to determine the inflation rate by tracking price changes in goods and services available for consumption in the market. In this context, all final monetary consumption expenditures carried out within the country by households, foreign visitors, and institutional units are taken into account. However, own-account household production and imputed rents are excluded from the CPI framework (Demir & Erdoğan, 2021).

The CPI is a weighted index calculated based on retail prices. Goods and services are assigned weights according to their shares in household consumption expenditures, and the index reflects the weighted average of price changes across these items (Ertek, 2019). The CPI basket is constructed from goods and services that are frequently consumed and considered relatively important by consumers, and it reports monthly or annual changes in average prices of these items (Kılıç et al., 2018; Alagöz et al., 2020).

The Consumer Price Index plays a critical role in the estimation of Gross Domestic Product (GDP) and in guiding monetary and fiscal policy decisions of central banks (Özpolat, 2020). Changes in price indices over time provide policymakers with valuable insights into the dynamics, structure, and sources of inflation. Moreover, monitoring price movements helps determine whether inflationary pressures in an economy are driven primarily by demand-side or cost-side factors (Erdem & Yamak, 2014).

The CPI is also a fundamental input for calculating numerous macroeconomic indicators, including the real effective exchange rate, purchasing power parity, and real GDP. In addition, it is used in socioeconomic analyses such as income inequality measurements (Iyengar & Bhattacharya, 1965; Tunalı & Özkan, 2016). However, particularly in developing countries, weaknesses in institutional structures, deficiencies in data collection processes, and political influences during the computation and dissemination stages may reduce the accuracy and reliability of CPI data.

Empirical evidence suggests that increases in the Consumer Price Index and the industrial production index may have differing effects on housing prices. While rises in industrial production and CPI tend to decrease housing prices, increases in housing loan interest rates and CPI have been found to raise housing prices. Furthermore, CPI and industrial production indices exhibited stationarity in certain periods and non-stationarity in others, influencing housing demand and price dynamics accordingly (Çetin, 2021).

The aim of this study is to model the Consumer Price Index (CPI) in Türkiye using time series analysis, to examine its long-memory properties through the ARFIMA framework, and to generate forecasts for future CPI dynamics.

II. Materials and Methods

The material of this study consists of the Consumer Price Index (CPI) values (2003 = 100) for Türkiye covering the period from January 2005 to September 2025. The data used in the analysis are monthly observations obtained from the Turkish Statistical Institute (TURKSTAT) via its official database. Statistical analyses were conducted using the R statistical software (R Core Team, 2020).

When developing a time series model, if the underlying stochastic process changes over time i.e., if the series is non-stationary the past and future structure of the series cannot be adequately explained by a simple algebraic model. However, if the stochastic process is time-invariant, a fixed-coefficient model based on past values of the series can be constructed (Kutlar & Turgut, 2006).

In a stationary time series, the difference between two consecutive observations depends solely on the time interval rather than on time itself; therefore, the mean of the series remains constant over time. In practice, however, most real-world time series are non-stationary, with means that change over time, often exhibiting upward or downward trends. Moreover, large fluctuations in the series may also lead to a loss of stationarity (Kutlar, 2005). In addition to non-stationary series, there exist long-memory processes, which exhibit persistence similar to non-stationarity but possess distinct statistical properties.

Autoregressive Fractionally Integrated Moving Average (ARFIMA) models, which are capable of jointly modeling short-run and long-run dependencies, were first introduced by Granger and Joyeux (1980). ARFIMA models are a class of long-memory models frequently applied in economic time series analysis. These models are based on Gaussian fractionally integrated processes and are typically estimated using Maximum Likelihood Estimation methods. The primary advantage of ARFIMA models lies in their ability to capture and forecast the long-term behavior of time series (Kutlar & Turgut, 2006).

Correlogram analyses are graphical tools used to examine the linear dependence structure of time series and display estimated autocorrelation functions. If the decay in the correlogram follows an exponential pattern, stationary ARMA or integrated ARIMA models, as suggested by Box and Jenkins, are considered appropriate. However, if the autocorrelations decay slowly at a hyperbolic rate, fractional integration analyses specifically ARFIMA models proposed by Granger and Ding (1996) are preferred.

The ARFIMA (p, d, q)model is one of the most important and flexible frameworks for discrete-time analysis. It was developed by Granger and Joyeux (1980), Granger (1980), and Hosking (1981). The general form of the ARFIMA (p, d, q)model is expressed as:

$$\phi(L)(1-L)^d(Y_t-\mu)=\theta(L)\varepsilon_t \qquad (1)$$

In Equation (1), the fractional differencing operator $(1-L)^d$is defined through a binomial expansion (Hosking, 1981):

$$(1-L)^d=\sum_{k=0}^{\infty}\binom{d}{k}(-L)^k$$

where $\binom{d}{k}$represents the fractional binomial coefficients, which can be expressed using the Gamma function as follows (Günay et al., 2007):

$$\binom{d}{k}=\frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)}$$

In Equation (1), Ldenotes the lag operator and $d$represents the fractional integration parameter. The polynomials $\phi(L)$and $\theta(L)$have all roots outside the unit circle, and $\varepsilon_t$is assumed to be a white noise process. When $d\neq 0$, the process $Y_t$is said to be integrated of order $I(d)$, in which case the autocorrelation coefficients decay slowly at a hyperbolic rate (Baillie, 1996).

The autoregressive and moving average lag polynomials are defined as:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p \qquad (2)$$

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q \qquad (3)$$

where μdenotes the mean of the series Y_t. In the ARFIMA (p, d, q)framework, $p$and $q$represent the autoregressive and moving average orders, respectively, and when $0 < d < 1$, the process exhibits long-memory behavior (Pong et al., 2008).

If the parameter $d$lies between 0 and 0.5, the series $Y_t$remains stationary, although its autocorrelation coefficients decay very slowly and do not converge rapidly to zero. When $d$is between 0.5 and 1, the series becomes non-stationary; however, shocks to the system dissipate over time, and the series exhibits mean-reverting behavior. If $d \geq 1$, the series loses its stationarity entirely, and the effects of shocks persist indefinitely (Barışık & Çevik, 2008).

To address volatility clustering and heteroskedasticity in time series, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later extended by Bollerslev (1986) through the Generalized ARCH (GARCH) model. Bollerslev (1986) demonstrated that modeling conditional variance using a moving average of past squared error terms provides a more accurate representation of volatility dynamics.

The GARCH (p, q)model is specified as follows (Bollerslev, 1986):

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 \qquad (4)$$

where σ_t^2denotes the conditional variance, $\omega$is a constant term, $\alpha_i$represents the coefficients of lagged squared error terms, $\beta_i$denotes the coefficients of lagged conditional variances, and $\varepsilon_t$is the error term.

Accordingly, the variance of the error term at time $t$depends on both the squared error term from the previous period and the conditional variance of the previous period (Gujarati & Porter, 2012). For the process to be stationary, the sum of the coefficients on the right-hand side of the conditional variance equation, excluding the constant term, must be less than or equal to one (Bollerslev, 1986):

$$\alpha_i + \beta_i \leq 1$$

III. Results and Discussion

The dynamic structure of the Consumer Price Index (CPI) series in Türkiye for the period January 2005–September 2025 was analyzed using the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. As an initial specification, the ARFIMA(1, d, 1) model was estimated to capture both short-run dynamics and long-memory behavior in the CPI series. The estimation results indicate the presence of fractional integration, suggesting that inflation dynamics in Türkiye exhibit persistent long-term dependence.

The parameter estimates obtained from the ARFIMA(1, d, 1) model are reported in Table 1. These results provide insights into the degree of persistence and the dynamic adjustment process of the CPI series over the sample period.

Table 1. Parameter estimates of the ARFIMA(1,d,1) model.

Parameter	Estimation	Explanation
d = 0.095	Fractional difference parameter	The series has a short memory structure. It is close to stationary but has slight persistent effects.
AR(1) = 1.028	Autoregressive coefficient	It is quite close to 1. The CPI series shows high autocorrelation and a strong trend effect.
MA(1) = -0.450	Mean correction	The series contains short-term corrections.

An examination of Table 1 shows that the estimated parameters of the ARFIMA(1, d, 1) model are $AR(1) = 1.028$and $MA(1) = -0.450$. The fractional differencing parameter is estimated as $d = 0.095$, indicating that the series exhibits short-memory behavior and appears to be close to stationarity. The estimated variance of the error term is $\sigma(\varepsilon) = 15.6$. As a measure of model adequacy, the Akaike Information Criterion (AIC) was calculated and found to be 2082.7.

To assess the stationarity of the CPI series, the Augmented Dickey–Fuller (ADF) test was applied. The test statistic was ADF = 1.4732, with a lag length of 6 and a corresponding p-value of 0.99, indicating that the null hypothesis

of a unit root cannot be rejected. Therefore, the CPI series is found to be non-stationary in levels, which justifies the use of a fractional integration framework.
The adequacy of the ARFIMA(1, d, 1) model was further evaluated through residual diagnostics using the Ljung–Box Q test. The test results are summarized as follows:

- Lag 10: $p = 4.76 \times 10^{-6}$
- Lag 20: $p = 2.99 \times 10^{-9}$
- Lag 30: $p = 2.32 \times 10^{-9}$

Since all p-values are less than 0.05, the null hypothesis of no autocorrelation in the residuals is rejected at conventional significance levels. These findings indicate the presence of remaining serial correlation in the residuals, suggesting that the ARFIMA(1, d, 1) model does not fully capture the dependence structure of the CPI series.
Consequently, in order to improve model performance and better account for the underlying dynamics of the series, higher-order specifications were considered. Specifically, the ARFIMA(2, d, 1) and ARFIMA(2, d, 2) models were sequentially estimated. The parameter estimates of the ARFIMA(2, d, 1) model are reported in Table 2.

Table 2. Parameter estimates of the ARFIMA(2,d,1) model.

Parameter	Estimation	Explanation
d = 0.274	Fractional difference parameter	It has a moderate long-term memory. The influence of past values on the CPI series persists for a long time.
AR(1) = 1.416	Autoregressive coefficient	High positive correlation: CPI increases are strongly linked to the previous period.
AR(2) = −0.400	The second autoregressive component has a stabilizing effect. This mitigates the fluctuations.	
MA(1) = 0.169	The short-term corrective effect is weak but positive.	

As shown in Table 2, the estimated parameters of the ARFIMA(2, d, 1) model are $AR(1) = 1.416$, $AR(2) = -0.400$, and $MA(1) = 0.169$. The fractional differencing parameter is estimated as $d = 0.274$, indicating the presence of moderate long-memory behavior in the CPI series.
The estimated variance of the error term is $\sigma(\varepsilon) = 14.22$, which represents a reduction compared to the ARFIMA(1, d, 1) model. This decline in the error variance suggests an improvement in the model's ability to capture the underlying dynamics of the CPI series. Furthermore, the Akaike Information Criterion (AIC) value is 2039.19, reflecting a substantial decrease of 43.52 units relative to the ARFIMA(1, d, 1) specification. This notable reduction in AIC provides strong evidence of enhanced model performance.
Residual diagnostics were conducted to assess the adequacy of the ARFIMA(2, d, 1) model, and the results of these analyses are presented in Table 3. These diagnostics are used to evaluate whether the remaining serial dependence in the residuals has been sufficiently eliminated, thereby determining the overall suitability of the model.

Table 3. Residual analysis of the ARFIMA(2,d,1) model.

Lag	χ^2	p	Explanation
10	29.27	0.0011	There is still weak autocorrelation.
20	57.20	1.9e−05	Reduced but not fully resolved.
30	72.32	2.4e−05	Partial autocorrelation is present.

In light of these findings, although the ARFIMA(2,d,1) model yields better results than the previous one, the ARFIMA(2,d,2) model will also be tested and the best model will be selected. The parameter estimates of the ARFIMA(2,d,2) model are presented in Table 4.

Table 4. Parameter estimates of the ARFIMA(2,d,2) model

Parameters	Estimation	Explanation
d = 0.289	Fractional difference parameter	The series exhibits a moderate long-term memory effect.
AR(1) = 1.413 AR(2) = -0.397	Autoregressive coefficients	The past two values in the series strongly influence the present value.
MA(1) = 0.165 MA(2) = 0.069	Moving average coefficients	The short-term effect of the shocks is weak but lasting.

As shown in Table 4, the ARFIMA(2,d,2) model yields AR(1)=1.413, AR(2)=−0.397, MA(1)=0.165, and MA(2)=0.069. The estimated fractional differencing parameter is d = 0.289, indicating the presence of long-memory behavior in the series. The variance of the error term is estimated as $\sigma^2(\varepsilon) = 14.19$, suggesting a relatively low level of forecast error. Moreover, the AIC value of 2028.29 is lower than those of the ARFIMA(1,d,1) and ARFIMA(2,d,1) models. This result indicates that the ARFIMA(2,d,2) model provides a better fit compared to the alternative specifications. The results of the diagnostic tests assessing model adequacy are reported in Table 5.

Table 5. Summary of diagnostic tests.

Test	Results	p-value	Explanation
Ljung–Box (10, 20, 30 lag)	χ^2 = 25–63	p < 0.01	Autocorrelation is present in the residuals, and the model can be improved.
ARCH LM (12 lag)	χ^2 = 52.5	p < 0.001	Heteroskedasticity (volatility) is present. GARCH-type models can be considered.

As shown in Table 5, the Ljung–Box test indicates that residual autocorrelation is still present in the ARFIMA(2,d,2) model ($p < 0.01$); however, it is lower compared to the ARFIMA(1,d,1) and ARFIMA(2,d,1) specifications. This finding suggests that the model partially reduces autocorrelation. The ARCH test results reveal the presence of heteroskedasticity ($p < 0.001$), indicating volatility clustering in the residuals. Therefore, although the ARFIMA(2,d,2) model provides good predictive performance, combining it with a volatility model such as GARCH may be more appropriate to capture ARCH effects. In summary, an ARFIMA–GARCH hybrid model can be applied to improve the modeling of conditional variance dynamics.

The ARFIMA(2,d,2) + GARCH(1,1) model is estimated to jointly capture both medium- and long-term inflation (CPI) dynamics and the volatility structure of the residuals. The parameter estimation results obtained from modeling long-memory behavior and conditional volatility are reported in Table 6.

Table 6. Estimation results of ARFIMA(2,d,2) + GARCH(1,1) model.

Parameters	Estimation	Standard error	t	p
μ	114.95342	0.414176	277.5471	0.000
AR(1)	2.02466	0.000652	3105.7385	0.000
AR(2)	-1.02481	0.000386	-2654.1777	0.000
MA(1)	-0.73865	0.036280	-20.3595	0.000
MA(2)	-0.21414	0.034577	-6.1932	0.000
ω	0.75234	0.211515	3.5569	0.001
α(1)	0.49141	0.047497	10.3463	0.000
β(1)	0.50759	0.036821	13.7852	0.000

As reported in Table 6, the estimated mean parameter (μ) indicates that the average level of the series is approximately 114.95 and is statistically significant. The autoregressive coefficients are estimated as AR(1) = 2.02466 (p = 0.000) and AR(2) = −1.02481 (p = 0.000). The extremely high t-statistics of both coefficients suggest that past values of the series strongly explain its current behavior. While the AR(1) coefficient is positive and large, the AR(2) coefficient is negative. This structure is commonly associated with high persistence, slowly dissipating shocks, and trend-like behavior in the series.

The moving average parameters are estimated as MA(1) = −0.73865 (p = 0.000) and MA(2) = −0.21414 (p = 0.000). Both MA coefficients are negative and statistically significant, indicating that past error terms affect the series in the opposite direction and that short-term irregularities are corrected relatively quickly.

Based on the information presented in Table 6, the mathematical representation of the ARFIMA(2,d,2) + GARCH(1,1) model can be expressed as follows. The mean equation of the ARFIMA(2,d,2) model is given by

$$(1-\phi_1 L-\phi_2 L^2)(1-L)^d(Y_t-\mu)=(1+\theta_1 L+\theta_2 L^2)\varepsilon_t,$$

and substituting the estimated parameter values into this expression yields

$$(1-2.02466L+1.02481L^2)(1-L)^{0.289}(Y_t-114.95342)=(1-0.73865L-0.21414L^2)\varepsilon_t.$$

The conditional variance equation following a GARCH(1,1) specification is defined as

$$\varepsilon_t=\sigma_t z_t, z_t\sim N(0,1),$$
$$\sigma_t^2=\omega+\alpha_1\varepsilon_{t-1}^2+\beta_1\sigma_{t-1}^2,$$

and substituting the estimated parameters yields

$$\sigma_t^2=0.75234+0.4914\varepsilon_{t-1}^2+0.50759\sigma_{t-1}^2.$$

The most critical parameter in the model, the fractional differencing degree, is estimated as d = 0.49999 (≈ 0.50). This value indicates that the series exhibits long-memory behavior, implying that the effects of shocks dissipate slowly and persist over a long period of time. Accordingly, the speed of mean reversion in the CPI series is considerably slower than that implied by classical ARMA models. Moreover, these findings suggest that the series displays stationary behavior. In other words, the fact that *d* is very close to 0.5 indicates that trend and persistence effects in CPI are remarkably strong and that economic shocks have long-lasting impacts. This result is particularly important in terms of the sustainability and effectiveness of inflation-related policy outcomes.

The estimated ARFIMA(2,d,2) + GARCH(1,1) model shows that all parameters in both the mean and variance equations are statistically significant. The magnitude of the autoregressive coefficients reveals a strong autoregressive structure, indicating that past values explain current values to a high degree. The moving average components highlight the important role of short-run error dynamics. Furthermore, the results from the GARCH(1,1) variance equation indicate that volatility is highly persistent, as the sum of the ARCH and GARCH parameters ($\alpha+\beta=0.49141+0.50759=0.999$) is very close to unity, implying that volatility shocks decay slowly and remain influential for extended periods. Overall, these findings confirm the presence of both long-memory characteristics and high volatility persistence in the series. Consequently, the ARFIMA–GARCH model successfully captures the complex dynamic structure of the CPI series.

When all results are evaluated together, it is evident that the ARFIMA(2, 0.49999, 2)–GARCH(1,1) model effectively captures both the long-term memory structure and the volatility dynamics of the CPI series. The model provides a robust statistical framework for both short-term forecasting and the assessment of long-run inflation dynamics. With the inclusion of the fractional integration parameter *d*, the estimated model parameters are as follows:

$$\mu=107.7712, \phi_1=1.0471, \phi_2=-0.0305,$$
$$\theta_1=-0.2739, \theta_2=-0.4158, d=0.4999,$$
$$\omega=0.7605, \alpha_1=0.5323, \beta_1=0.4667.$$

Given *d* = 0.4999, the mathematical representation of the ARFIMA(2,0.4999,2) + GARCH(1,1) model is expressed as

$$(1-1.0471L+0.0305L^2)(1-L)^{0.49999}(Y_t-107.7712)=(1-0.2739L-0.4158L^2)\varepsilon_t,$$

and the corresponding volatility equation is given by

$$\sigma_t^2=0.7604+0.5323\varepsilon_{t-1}^2+0.4667\sigma_{t-1}^2.$$

Finally, the overall goodness-of-fit performance of the model is evaluated using the results reported in Table 7.

Table 7. Model fit tests.

Test	Results
Ljung-Box (standardized residues)	No autocorrelation
Ljung-Box (squares)	No autocorrelation
ARCH LM	GARCH effect present
Nyblom Stability	Parameters stable
Sign Bias Test	No symmetry error
Log Likelihood	-713.153
Akaike Information Criterion (AIC)	5.7924
Bayes Information Criterion (BIC)	5.9054

As reported in Table 7, the Ljung–Box test results indicate no residual autocorrelation in either the standardized residuals or their squared values, suggesting that the model is well specified. The ARCH LM test confirms the presence of significant GARCH effects, indicating conditional heteroskedasticity in the variance process. The Nyblom stability test and the Sign Bias test results reveal that the estimated parameters are stable over time and that no asymmetry bias is present in the model.

Furthermore, based on the AIC and BIC criteria, the ARFIMA(2,d,2) + GARCH(1,1) model provides a better fit compared to the previously estimated ARFIMA specifications. Consequently, the ARFIMA(2,d,2) + GARCH(1,1) model is an appropriate framework for jointly modeling the mean and volatility dynamics of the CPI series. Based on this estimated model, forecasts for the year 2026 can also be generated, as reported in Table 8.

Table 8. Forecasting for CPI values in 2026.

Months	Forecast
January	3457.25
February	3543.09
March	3630.54
April	3719.64
May	3810.41
June	3902.88
July	3997.07
August	4093.03
September	4190.77
October	4290.33
November	4391.73
December	4495.01

An examination of Table 8 reveals a steady and strong upward trend in the CPI level throughout 2026. The forecasts indicate that the CPI, which stands at 3,457.25 at the beginning of the year, is expected to reach 4,495.01 by the end of the year. This implies an overall increase of approximately 30 percent over the year.

All monthly forecast values exhibit an upward movement, with no declines observed in any period. This pattern suggests that price levels in Türkiye are both trend-dominant and subject to intense inflationary pressures. The long-memory property captured by the ARFIMA structure implies that the effects of past price shocks persist over extended horizons, while the GARCH component reflects the persistence of volatility. Taken together, these features provide econometrically consistent support for an upward CPI trajectory in 2026.

The largest monthly increases are particularly pronounced in the second half of the year. The forecasted rises during the August–December period indicate that both seasonal factors and price rigidity from previous periods remain strongly influential. Overall, the model suggests that the upward trend observed throughout the year is structural and persistent in nature.

IV. Conclusion

This study examines Türkiye's Consumer Price Index (CPI) series over the period 2005–2025 using the ARFIMA(2,d,2) model. The estimated parameters are $d = 0.289$, AR(1) = 1.413, AR(2) = −0.397, MA(1) = 0.165, and MA(2) = 0.069. These results indicate the presence of positive long-memory behavior, implying that past inflation dynamics continue to influence future CPI movements. This finding is consistent with the existing literature documenting long-memory characteristics in inflation series.

To account for time-varying volatility in the CPI series, the ARFIMA(2,d,2) + GARCH(1,1) model is employed. All coefficients in the mean equation are statistically significant at the 5% level, while the volatility parameters are also found to be significant, with $\alpha_1 = 0.491$ and $\beta_1 = 0.508$. The Ljung–Box and ARCH test results indicate no residual autocorrelation or remaining ARCH effects in the standardized residuals, suggesting that the model is well specified.

While the ARFIMA(2,d,2) model successfully captures the conditional mean dynamics, it does not account for time-varying volatility. The inclusion of the GARCH(1,1) component reveals that the conditional variance is predictable over time and enhances the reliability of the inflation forecasts.

The Ljung–Box and ARCH test results further suggest that the model residuals approximate white noise, supporting the adequacy of both the ARFIMA(2,0.4999,2) and the ARFIMA–GARCH(1,1) specifications. Finally, the CPI forecasts and volatility projections for 2026 provide valuable insights for short-term planning and risk assessment. The projected upward trajectory of CPI throughout 2026 highlights the importance of inflation expectations for monetary policy formulation and broader economic planning.

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