Modeling and Forecasting the Consumer Price Index in Algeria
A Seasonal ARMA–ARCH(1) Approach

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Received : 10.05.2026 Accepted: 12.06.2026 Published : 01.07.2026

Abstract: This article presents a model and forecast of the Consumer Price Index (CPI) in Algeria for the period 2002–2025, based on monthly data from the IMF and World Bank databases. After verifying the stationarity of the series (ADF and PP tests), we identify strong seasonality (12-month periodicity) and conditional heteroscedasticity (ARCH effects) in the residuals of a preliminary ARMA model. The specification chosen for the conditional mean is an ARMA(2,0) model augmented with a seasonal component SAR(12) and SMA(12). For the conditional variance, an ARCH(1) process is estimated and proves preferable to a GARCH(1,1) model, which suffers from convergence issues and violations of the positivity and stationarity constraints. Validation tests on the standardized residuals confirm the absence of residual ARCH effects (ARCH test: p = 0.88) and acceptable normality (Jarque-Bera: p = 0.11). Forecasts for the first six months of 2026 indicate stable monthly inflation with volatility converging toward its long-run value. This research makes an original contribution to the literature on inflation in emerging and rentier economies by demonstrating the relevance of a seasonal ARMA–ARCH(1) model for capturing both the mean dynamics and the volatility of the Algerian CPI.

Keywords: Consumer Price Index, seasonal ARMA, ARCH(1), inflation

JEL Classification Codes:E31, C22, C53.

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1. Introduction

Controlling inflation is one of the fundamental objectives of economic policy, particularly in developing countries where price instability directly affects household purchasing power, investment decisions, and external competitiveness. In Algeria, inflation has followed a mixed trajectory over the past two decades: after peaking at over 11% in 2012, the inflation rate fell and then accelerated again to 9.3% in 2023, before dropping back to around 4% in 2024(IMF,2023). Current projections call for moderate inflation of about 3.9% in 2026, supported by the stabilization of the official exchange rate and lower food prices(World Bank,2025). However, persistent inflationary pressures linked to food prices and adjustments to administered prices (fuel) make it necessary to closely monitor CPI trends.

In this context, econometric time-series models are useful tools for forecasting inflation. While classical ARMA models can capture the linear dynamics of the conditional mean, they do not account for a property frequently observed in macroeconomic and financial time series: time-varying volatility (clusters of high variance). To address this limitation, Engle (1982) proposed the class of ARCH (Autoregressive Conditional Heteroskedasticity) models, generalized by Bollerslev (1986) as GARCH (Generalized ARCH), which simultaneously model the conditional mean and variance. This hybrid ARMA-GARCH approach has been widely used for inflation forecasting in various national contexts, whether in Pakistan((Shahbaz et al., 2014), Nigeria ((Kilani et al., 2025), or Côte d'Ivoire(Amadou Kamagaté et al., 2025). However, to our knowledge, no study has systematically applied this methodology to the Algerian CPI.

The objective of this study is to identify the appropriate dynamic structure of the conditional mean of Algeria's CPI by incorporating its strong monthly seasonality, to model the conditional volatility of inflation using an ARCH process, and to evaluate the predictive performance of the selected model while discussing its implications for monetary policy in Algeria. Methodologically, the approach unfolds in several stages: unit root tests, identification of ARMA and SARMA orders based on autocorrelations and information criteria (AIC/BIC), estimation of the SARMA-ARCH and SARMA-GARCH models via maximum likelihood (BFGS algorithm), followed by validation through analysis of standardized residuals (Jarque-Bera normality test, Lagrange ARCH test, correlogram). The sample covers the period from January 2002 to December 2025, comprising 287 monthly observations. The forecast is conducted over a one-year horizon (2026).

This article fills this gap in the literature for three main reasons. First, it uses a long monthly time series (2002–2025) that covers both periods of high inflation and episodes of disinflation, allowing for a robust estimation of the parameters. Second, it explicitly accounts for seasonality (12-month periodicity) by introducing SAR and SMA components, which is crucial for consumer price series. Third, it validates the model based on a comprehensive set of diagnostic tests (normality of standardized residuals, absence of residual ARCH effects, structural stability) and quantifies forecasting performance using standard metrics (MAPE, Theil U1). The concluding discussion addresses the implications of these results for the conduct of monetary policy in Algeria, particularly within the framework of the new inflation-targeting framework that the Bank of Algeria is seeking to adopt.

The main results show that the D(CPI) series—the first difference of the CPI—is stationary and exhibits a seasonal structure with a period of 12. The best-fitting model is an ARMA(2,0) model augmented with a seasonal component consisting of SAR(12) and SMA(12). The introduction of an ARCH(1) model eliminates residual heteroscedasticity and normalizes the residuals. Accuracy measures (symmetric MAPE = 5.2%) confirm the model's predictive quality. These results suggest that hybrid models are a reliable tool for forecasting inflation in Algeria, complementing macro-structural models.

2. Data and Methodology

2.1 Data

The data series analyzed is the Consumer Price Index (CPI) for Algeria (base year 2001). The data are drawn from the International Monetary Fund's database and cover the period from January 2002 to December 2025, comprising 288 monthly observations. This period was chosen to include both years of relative stability (2002–2019) and recent inflationary shocks (2021–2025), while avoiding structural breaks associated with the economic transition of the 1990s.

2.2 Model

This subsection defines the ARMA, ARCH, GARCH, ARMA-ARCH, hybrid ARMA-GARCH, and rolling forecast models used in this study. In the hybrid ARMA-GARCH specification, the observed series follows an ARMA process for the conditional mean, while the conditional variance of the errors follows an ARCH process

2.2.1. SARIMA Model : Autoregressive Integrated Moving Average (ARIMA) models are an extension of ARMA models. ARIMA models are obtained by differentiating non-stationary time series. The seasonal model for seasonal time series is defined by SARIMA (p,d,q)(P,D,Q)s. The SARIMA model is expressed as a combination of non-seasonal and seasonal parameters, as shown in the equation below:

$$\Phi_p(B^s)\phi(B)\nabla_S^D\nabla^d X_t = \alpha + \Theta_\varrho(B^s)\theta(B)w_t$$

It is denoted as ARIMA(p,d,q)*(P,D,Q)

$$\nabla^d = (1-B)^d;\ \nabla_S^D = (1-B^s)^D$$

Xt denotes the observation at time t,

ε_t defines the random error at time t (unobserved data),

∇^d: is the differentiation operator of order d,

∇_s^D : is the seasonal differentiation operator of order D,

In the notation of the equation (p,d,q)(P,D,Q)s, p denotes the non-seasonal AR order, d denotes the differentiation order, and q denotes the MA order; P denotes the seasonal AR order, D denotes the seasonal differentiation order, and Q denotes the seasonal MA order; and s is the length of the seasonal period.

2.2.2 ARCH(q) Model : Proposed by Engle (1982), this model represents conditional variance as a linear function of the squares of past residuals (up to order q, the model is written as :

• **Equation for the mean** :$y_t=\mu + \varepsilon_t$ avec $\varepsilon_t = \sigma_t z_t$, $z_t \sim$i.i.d(0,1)

σ_t is the conditional standard deviation (volatility).

z_t is the standardized shock: it represents the unpredictable random component, with a mean of zero and a variance of one.

• **Variance équation** :

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots \ldots \ldots + \alpha_q \varepsilon_{t-q}^2$$

$$o\grave{u}\ \omega > 0, \alpha_i > 0, et \sum_{i=1}^{q} \alpha_i < 1\ pour\ la\ stationnarité$$

2.2.3 GARCH (p, q) Model: Proposed by Bollerslev (1986), this model generalizes the ARCH model by incorporating past conditional variances (of order p) to capture the volatility of the time series. The general form of the error term and its conditional variance σ_t^2 is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Where:

$$\omega > 0, \alpha_i > 0, \beta_j > 0\ et \sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1\ pourlastationnarité$$

The widely used GARCH(1,1) model is often sufficient for modeling the persistence of volatility observed in financial time series, thanks to the term $\beta_1 \sigma_{t-1}^2$This results in fewer parameters compared to an ARCH(q) model with a high value of q.

2.2.3. ARIMA-GARCH Model : The ARIMA-GARCH model is defined by two main components: the ARIMA model for the mean equation and the GARCH model for the variance equation. The ARIMA model is given by :

$$(1 - \sum_{i=1}^{p} L^d \phi_i)\ (1 - L^d)^q y_t = (\sum_{j=0}^{q} L^j \theta_j)\varepsilon_t$$

where L is the lag operator, ϕ_i are the AR coefficients, θj are the MA coefficients, d is the order of differentiation, and ε_t is the residual or error term from the ARIMA model. Meanwhile, the GARCH model in equation (2) isdefinedby:

$$\varepsilon_t = V_t \sqrt{h_t}$$

so that :$\sigma_v^2 = 1$ et $\quad h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2$ ……(2)

Under these condition , it is important to ensure that $\alpha_0>0$, $\alpha i \geq 0$, $\beta j \geq 0$ and

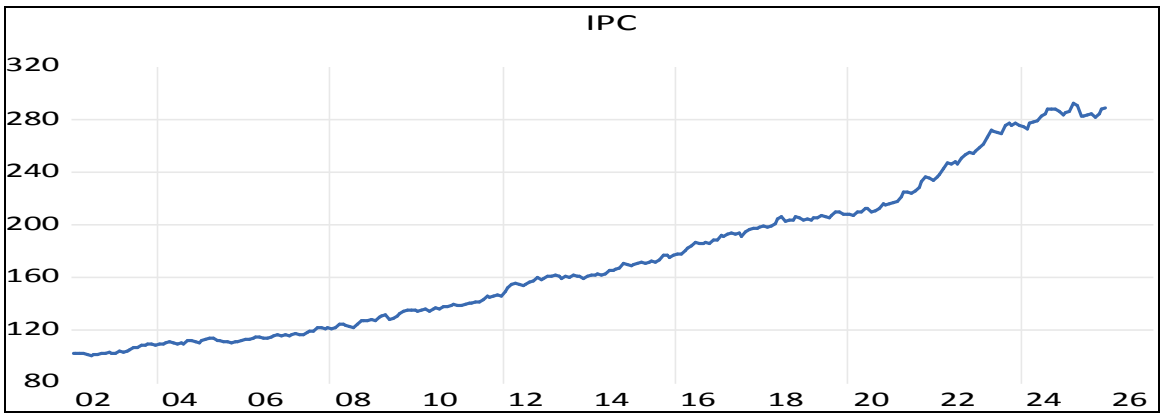
$$1 - \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j > 0$$

so that the conditional variance is positive. Since V_t is white noise, the key point is that the conditional variance of ε_t is given by: $Var_{t-1}(\varepsilon t)=ht$

3. Results and Discussion

This section presents the results of the empirical analysis. We first examine the stationarity and seasonality properties of the CPI, then identify the dynamic structure of the conditional mean before modeling volatility using an ARCH process. Finally, we validate the selected model and discuss its forecasts for the year 2026.

Figure 01. CPI Trends from January 2002 to December 2025

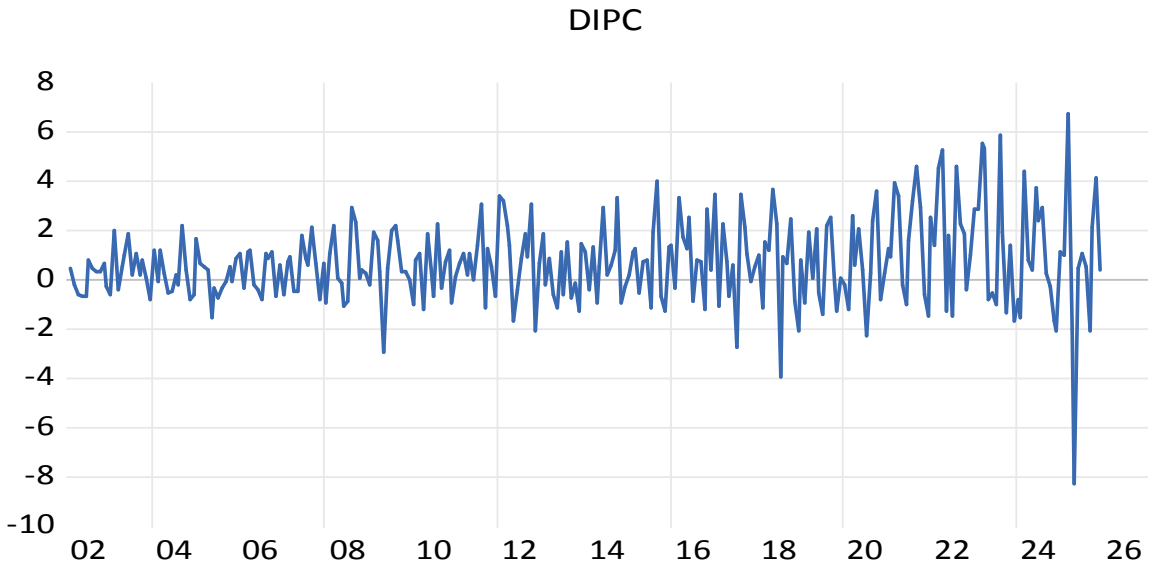


A descriptive analysis of Figure 1 reveals a steady increase in the CPI over the study period, followed by a marked acceleration after 2021. The raw time series is not stationary, as confirmed by the ADF (Augmented Dickey-Fuller) test (Table 1) applied at the level (p-value > 0.05). In contrast, the first-difference series (D(CPI)) is stationary (p-value < 0.05). Figure 2 shows the evolution of D(CPI); peaks in volatility are observed around 2008, 2012, 2022, and 2023 (Figure 2), suggesting the presence of ARCH effects

Table 01. Results of the ADF and PP tests

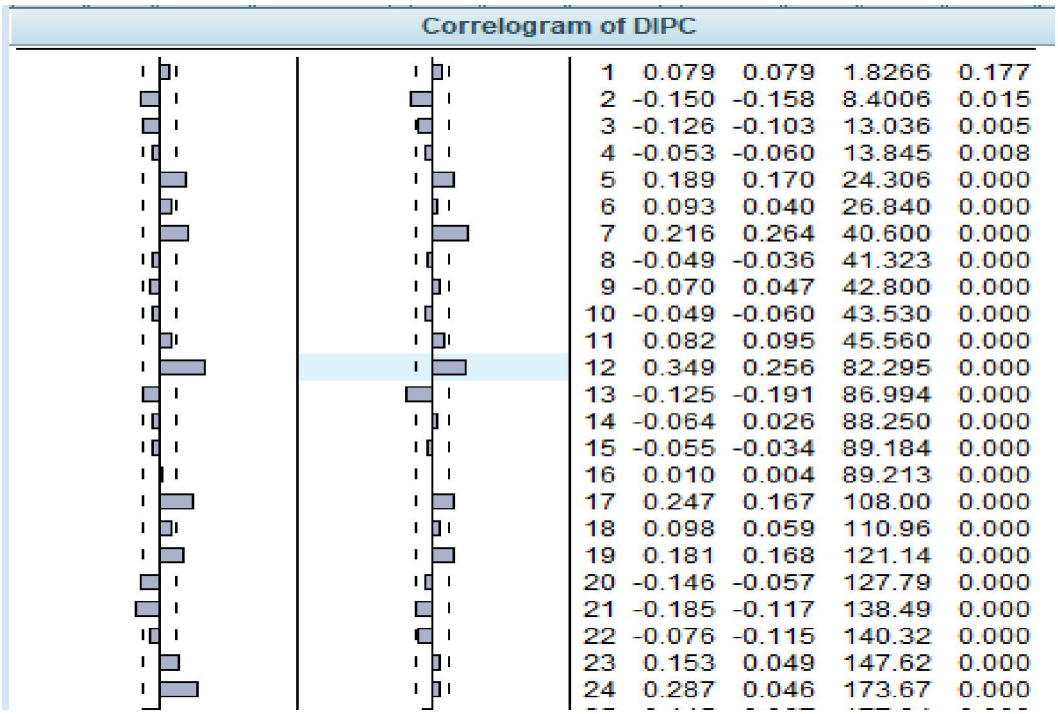
	Niveaux (p-value)		Différence première (p-value)		
	ADF	PP	ADF	PP	Décision
Trend end intercept	0,814	0,88	0,02	0,0000	I(1)

Figure 02. Change in the CPI (first difference)



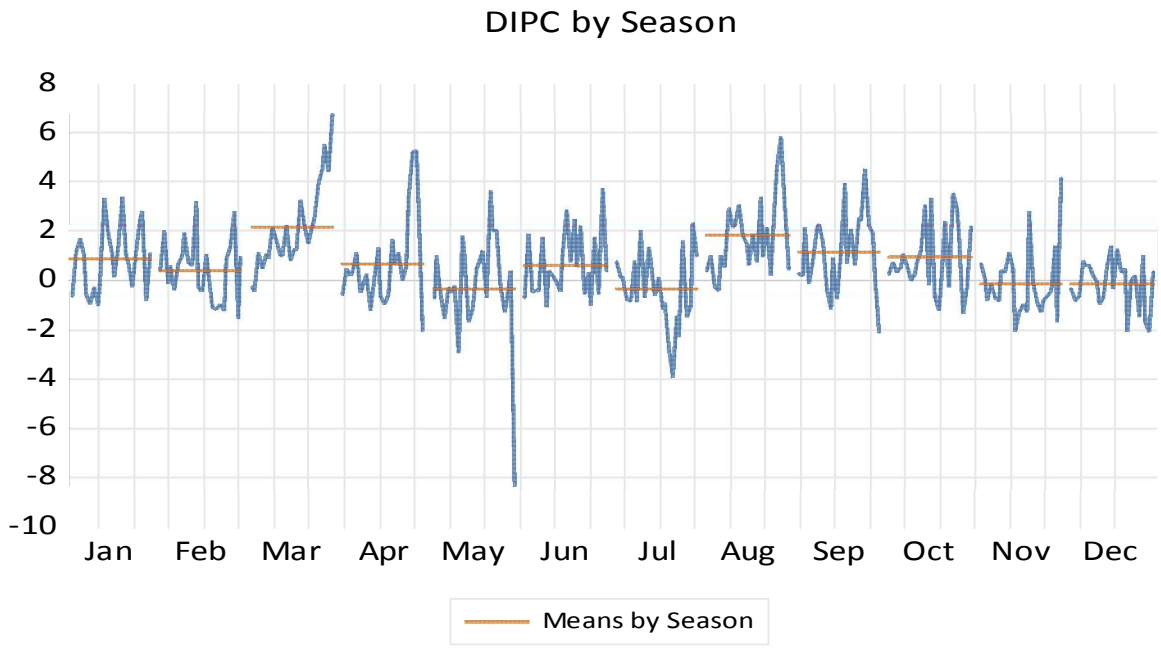
We analyze the autocorrelation function (ACF) and partial autocorrelation function (PACF). The presence of significant peaks at lags 1, 2, 12, and 24 indicates a low-order ARMA structure combined with strong seasonality. The graph of the seasonal d(CPI) series shows the presence of seasonality.

Figure 03. Correlogram of the differentiated CPI



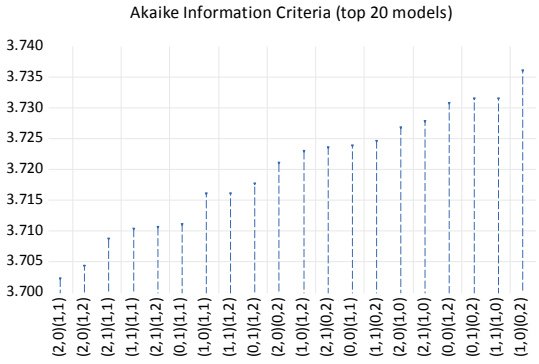
1	0.079	0.079	1.8266	0.177
2	-0.150	-0.158	8.4006	0.015
3	-0.126	-0.103	13.036	0.005
4	-0.053	-0.060	13.845	0.008
5	0.189	0.170	24.306	0.000
6	0.093	0.040	26.840	0.000
7	0.216	0.264	40.600	0.000
8	-0.049	-0.036	41.323	0.000
9	-0.070	0.047	42.800	0.000
10	-0.049	-0.060	43.530	0.000
11	0.082	0.095	45.560	0.000
12	0.349	0.256	82.295	0.000
13	-0.125	-0.191	86.994	0.000
14	-0.064	0.026	88.250	0.000
15	-0.055	-0.034	89.184	0.000
16	0.010	0.004	89.213	0.000
17	0.247	0.167	108.00	0.000
18	0.098	0.059	110.96	0.000
19	0.181	0.168	121.14	0.000
20	-0.146	-0.057	127.79	0.000
21	-0.185	-0.117	138.49	0.000
22	-0.076	-0.115	140.32	0.000
23	0.153	0.049	147.62	0.000
24	0.287	0.046	173.67	0.000

Figure 04. Seasonal CPI



We use the AIC (Akaike) and BIC (Schwarz) information criteria to select the orders p, q, P, and Q of a SARMA model from among the candidate combinations (p, q ∈ {0, 1, 2}, P, Q ∈ {0, 1, 2}). The selected model minimizes the AIC while ensuring the individual significance of the parameters (Student's t-test).

Figure05.Comparison of 20 models selected based on the AIC criterion and model estimation



Model Selection Criteria Table
Dependent Variable: D(INF)
Date: 05/09/26 Time: 11:13
Sample: 2002M01 2025M12
Included observations: 287

Model	LogL	AIC*	BIC	HQ
(2,0)(1,1)	-525.248195	3.702078	3.778583	3.732740
(2,0)(1,2)	-524.553481	3.704205	3.793461	3.739978
(2,1)(1,1)	-525.180369	3.708574	3.797830	3.744346
(1,1)(1,1)	-526.408195	3.710162	3.786666	3.740824
(2,1)(1,2)	-524.460532	3.710526	3.812533	3.751409
(0,1)(1,1)	-527.519499	3.710937	3.774691	3.736489
(1,0)(1,1)	-528.240318	3.715960	3.779714	3.741512
(1,1)(1,2)	-526.240983	3.715965	3.805221	3.751737
(0,1)(1,2)	-527.476449	3.717606	3.794111	3.748268

Dependent Variable: D(IPC)
Method: ARMA Maximum Likelihood (BFGS)
Date: 05/10/26 Time: 12:19
Sample: 2002M02 2025M12
Included observations: 287
Convergence achieved after 34 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.611592	0.225059	2.717481	0.0070
AR(1)	0.136914	0.049016	2.793236	0.0056
AR(2)	-0.146529	0.052869	-2.771518	0.0060
SAR(12)	0.805951	0.075630	10.65654	0.0000
MA(12)	-0.503638	0.115909	-4.345130	0.0000
SIGMASQ	2.247139	0.161811	13.88744	0.0000

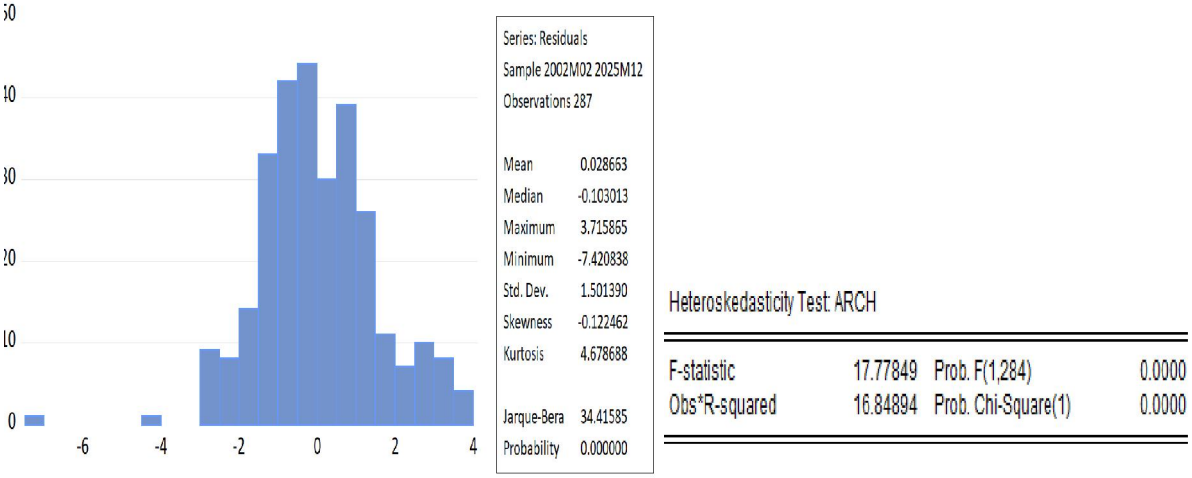
R-squared	0.212721	Mean dependent var	0.649965
Adjusted R-squared	0.198712	S.D. dependent var	1.692421
S.E. of regression	1.514965	Akaike info criterion	3.702078
Sum squared resid	644.9288	Schwarz criterion	3.778583
Log likelihood	-525.2482	Hannan-Quinn criter.	3.732740
F-statistic	15.18510	Durbin-Watson stat	2.004918
Prob(F-statistic)	0.000000		

Model identification using the AIC and BIC criteria leads to the selection of an ARMA(2,0) model with SAR(12) and SMA(12) seasonal components. Thus, all coefficients of the estimated model are significant ($p < 0.05$).

Model validation test:

Step 1: The Jarque-Bera normality test applied to the residuals yields a probability of less than 0.05 (p-value < 0.05), which allows us to reject the null hypothesis of normality

Figure 06. Normality and heteroscedasticity tests for the seasonal ARMA model



The ARCH heteroscedasticity test performed on the residuals indicates the presence of residual heteroscedasticity. (probF< 0.05)

Step 2: Modeling CPI Volatility

After specifying a seasonal ARMA model for the first difference of the Consumer Price Index (CPI), diagnostic tests on the residuals jointly rejected the assumption of normality (Jarque–Bera test) and that of homoscedasticity (ARCH test). These results justify the use of conditional heteroscedasticity modeling.

We successively estimate an ARCH(1) process and a GARCH(1,1) process under the assumption of Gaussian innovations. Table 2 presents the results obtained:

Table 02. Comparison of the ARCH(1) and GARCH(1,1) models

Model	AR(1)	AR(2)	SAR(12)	MA(12)	α_1	β_1	$\alpha_1+\beta_1$	AIC
ARCH(1)	0.146 (0.025)	-0.181 (0.001)	1.027 (0.000)	-0.887 (0.000)	0.316 (0.001)	–	0.316	3.609
GARCH(1,1)	0.078 (0.253)	-0.143 (0.037)	1.013 (0.000)	-0.869 (0.000)	-0.017 (0.433)	1.037 (0.000)	1.020	3.475

Dependent Variable: D(IPC)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 05/10/26 Time: 12:49
Sample (adjusted): 2003M04 2025M12
Included observations: 273 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2002M04 2003M03
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.145905	0.065033	2.243555	0.0249
AR(2)	-0.181335	0.053516	-3.388452	0.0007
SAR(12)	1.026693	0.013127	78.21257	0.0000
MA(12)	-0.887192	0.031357	-28.29287	0.0000
Variance Equation				
C	1.544681	0.169596	9.107980	0.0000
RESID(-1)^2	0.316303	0.095895	3.298432	0.0010

R-squared	0.235964	Mean dependent var	0.678645
Adjusted R-squared	0.227444	S.D. dependent var	1.722645
S.E. of regression	1.514122	Akaike info criterion	3.608903
Sum squared resid	616.7005	Schwarz criterion	3.688232
Log likelihood	-486.6152	Hannan-Quinn criter.	3.640747
Durbin-Watson stat	1.985392		

Dependent Variable: D(IPC)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 05/10/26 Time: 12:50
Sample (adjusted): 2003M04 2025M12
Included observations: 273 after adjustments
Failure to improve likelihood (non-zero gradients) after 83 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2002M04 2003M03
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.077958	0.068176	1.143493	0.2528
AR(2)	-0.142957	0.068642	-2.082650	0.0373
SAR(12)	1.012942	0.000740	1369.643	0.0000
MA(12)	-0.868615	0.022737	-38.20234	0.0000
Variance Equation				
C	-0.024493	0.018793	-1.303305	0.1925
RESID(-1)^2	-0.016850	0.021467	-0.784935	0.4325
GARCH(-1)	1.036945	0.031504	32.91476	0.0000

R-squared	0.225277	Mean dependent var	0.678645
Adjusted R-squared	0.216637	S.D. dependent var	1.722645
S.E. of regression	1.524675	Akaike info criterion	3.474762
Sum squared resid	625.3266	Schwarz criterion	3.567313
Log likelihood	-467.3050	Hannan-Quinn criter.	3.511914
Durbin-Watson stat	1.857718		

The ARCH(1) model converges without difficulty and satisfies all positivity and stationarity constraints: $\widehat{\alpha 1}$= 0.316 < 1. All coefficients of the conditional mean are significant at the 5% level, with moderate linear persistence (AR(1) = 0.146) and a strong annual seasonal component (SAR(12) = 1.027, MA(12) = -0.887), indicating a seasonal moving average-type dynamic to correct for excess seasonal autocorrelation.

In contrast, the estimation of the GARCH(1,1) model encounters convergence difficulties (zero gradients not reached after 83 iterations). Most importantly, the parameters of the variance equation violate the standard conditions of a GARCH process: the coefficient$\widehat{\alpha 1}$ is negative (-0.017, not significant), the variance constant is negative (-0.024, not significant), and the sum $\widehat{\propto_1}+\widehat{\beta_1}$ =1.020 exceeds unity, suggesting non-stationarity of the conditional variance. Although the log-likelihood is higher (i.e., a lower AIC), these anomalies indicate that the GARCH(1,1) specification is not econometrically valid for this series.

Based on the criteria for internal validity (positivity constraints, stationarity, convergence), we select the ARCH(1) model as an appropriate representation of the conditional variance of DIPC. This model effectively captures short-term leverage (one-month volatility shock) without introducing numerical instability.

The selected specification is written as:

- **Mean equation :**

$$DIPC_t=0.145905\cdot DIPC_{t-1}-0.181335DIPC_{t-2}+1.026693DIPC_{t-12}+\varepsilon t-0.887192\cdot\varepsilon_{t-12}$$

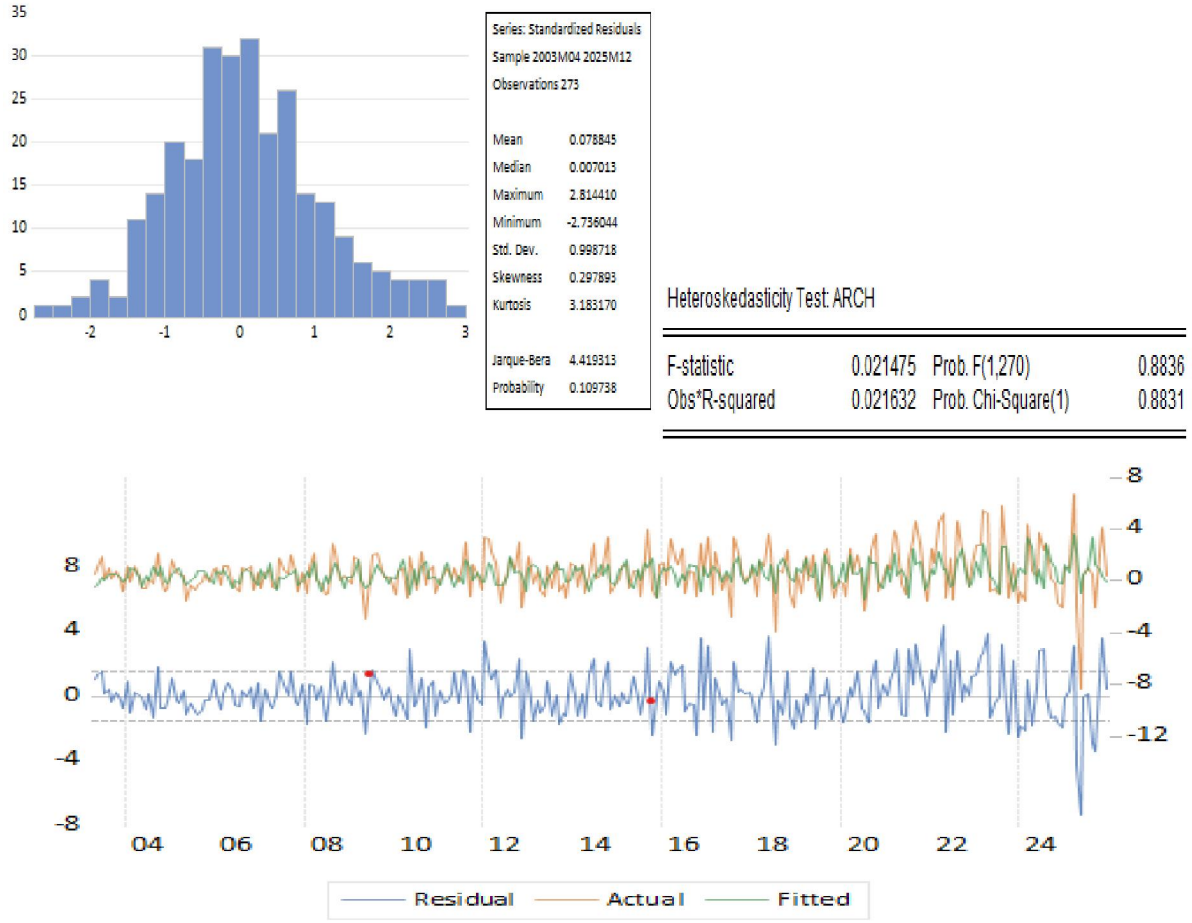
- **Variance equation :**

$$\sigma_t^2 = 1.544681 + 0.316303\varepsilon_{t-1}^2$$

The standardized residuals from the seasonal ARMA–ARCH(1) model satisfy the assumptions of normality (Jarque–Bera: 4.42, p = 0.11) and no autocorrelation of squares (ARCH test of order 1: LM = 0.02, p = 0.88). These results indicate that the ARCH(1) model effectively eliminates the conditional heteroscedasticity present in the raw residuals, and that the distribution of the standardized innovations is consistent with a normal distribution. Therefore,

the chosen specification can be considered well-calibrated to represent the dynamics of CPI volatility.

Figure 06. Normality and heteroscedasticity tests of the seasonal ARMA–ARCH(1) model



As we observe from the residual plot, the difference between the actual values and the residuals are small, almost identical. This indicates that the model is valid for forecasting the CPI in the coming months.

4. Forecast

The forecast is produced for the year 2026, from January to June. The forecasted values are:

date	Forcast
2026M01	288.8612
2026M02	289.0254
2026M03	293.1134
2026M04	294.5636
2026M05	293.6271
2026M06	294.6153

5. Conclusion

This study proposes an econometric modeling of the Consumer Price Index (CPI) in Algeria over the period 2002–2025, combining a seasonal ARMA specification for the conditional mean and an ARCH(1) process for the conditional variance. The results confirm that the first-differenced series (DIPC) is stationary and exhibits a marked seasonal pattern of period 12, correctly captured by the SAR(12) and SMA(12) components. Although a GARCH(1,1) model was tested, its convergence issues and violation of positivity and stationarity constraints (negative α, $\alpha+\beta> 1$) led to the selection of the more parsimonious and econometrically valid ARCH(1) model.

From a theoretical perspective, this research contributes to the literature on inflation modeling in emerging and resource-dependent economies by demonstrating that an ARCH(1) process may suffice to capture volatility persistence when the GARCH(1,1) process proves unstable. It also underscores the importance of accounting for monthly seasonality in consumer price series, which is often neglected in standard applications.

From a practical standpoint, the forecasts produced for the year 2026 provide Algerian monetary authorities with an operational short-term forecasting tool. The predicted conditional variance converges rapidly to its long-run unconditional value (≈ 2.26), suggesting moderate and stable volatility.

In conclusion, this work confirms the relevance of hybrid ARMA–ARCH models for forecasting inflation in Algeria and provides a solid methodological foundation for conducting monetary policy based on volatility expectations.

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