

Short-term Forecast and Inflation Trend Analysis of China's CPI Based on ARIMA Model

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Abstract:

The Consumer Price Index (CPI) is a critical indicator for macroeconomic regulation. While time series analysis is widely used for short-term forecasting, existing studies on China's CPI often overlook significant seasonal fluctuations or lack rigorous out-of-sample validation. This study addresses these gaps by applying the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to China's monthly CPI data from February 1996 to August 2025. Following the Box-Jenkins methodology, the data is split into training and test sets to ensure robust evaluation. Empirical results identify the optimal model as SARIMA(1,0,2)(1,0,1)₁₂. In a 24-month out-of-sample forecast, the SARIMA model significantly outperforms the non-seasonal ARIMA model, reducing the Root Mean Squared Error (RMSE) by approximately 14.1% (0.384 vs. 0.447) and the Mean Absolute Error (MAE) by 15.2%. This confirms the necessity of incorporating seasonal factors for accurate monthly CPI forecasting. Based on the optimal model, the 12-month-ahead forecast indicates that China's CPI will follow a trajectory of low-level, moderate recovery, stabilizing within the 1.0%–1.5% range by mid-2026. The findings suggest no immediate risk of sustained deflation but highlight limited upward pressure, providing a quantitative basis for monetary policy fine-tuning.

Keywords: CPI; SARIMA model; Short-term forecasting; Inflation trends.

1. Introduction

1.1 Research Background

The Consumer Price Index (CPI) serves as a primary gauge for inflation and a key reference for monetary

policy. Over the past three decades, China's CPI has experienced complex fluctuations driven by economic cycles and external shocks. Accurate short-term forecasting of CPI is essential for managing market expectations. Among various quantitative tools, the Autoregressive Integrated Moving Average (ARIMA)

model and its seasonal extension (SARIMA) remain the benchmarks for linear time series forecasting due to their robustness. However, existing literature on China's CPI often suffers from two limitations: neglecting the inherent seasonality in monthly data by applying non-seasonal models, or relying solely on in-sample fitting without rigorous out-of-sample validation. This study aims to fill this gap by systematically applying the SARIMA model to China's monthly CPI, rigorously testing its superiority over non-seasonal benchmarks.

1.2 Research Significance

Theoretically, this study provides a reproducible application of the Box-Jenkins methodology, quantitatively demonstrating the marginal value of modeling seasonal components in inflation data. Practically, accurate short-term forecasts assist policymakers in fine-tuning monetary instruments and help market entities optimize asset allocation.

1.3 Research Content and Structure

This paper addresses four central questions: the time-series characteristics and seasonal patterns of China's monthly CPI; the appropriate form of SARIMA model and its diagnostic tests; the forecasting advantages of SARIMA over non-seasonal ARIMA and seasonally adjusted ARIMA; and the short-term future inflation outlook based on the optimal model. The paper consists of eight chapters: following the introduction are literature review, theoretical methodology, preliminary data analysis, model specification and diagnostics, out-of-sample forecasting and trend analysis, further discussion, and concluding recommendations.

2. Literature Review

Inflation forecasting methods fall into three broad categories. Structural models (e.g., Phillips Curve, DSGE) offer interpretability but suffer from misspecification [1-3]. Machine learning (e.g., SVR, LSTM) captures nonlinearity yet lacks transparency for policy use [4,5]. Time series models, especially the ARIMA family, remain the benchmark for short-term forecasting due to their robustness and simplicity [6-8].

The ARIMA(p,d,q) model [9] and its seasonal extension SARIMA(p,d,q)(P,D,Q)_s accommodate periodic patterns via seasonal differencing and seasonal AR/MA terms. The Box-Jenkins procedure provides a standard framework. SARIMA is preferred when monthly data exhibit recurring annual cycles [10,11].

In China's CPI forecasting, ARIMA-type models have been widely applied [12,13,14]. However, most studies emphasize in-sample fit over out-of-sample validation.

Moreover, many directly apply non-seasonal ARIMA to monthly data, assuming year-on-year calculations eliminate seasonality—a premise questioned by Wang [15], who identified persistent Spring Festival effects. While some recent work employs SARIMA (e.g., for Korea [10] and US PPI [11]), systematic comparisons of SARIMA versus non-seasonal ARIMA using rigorous out-of-sample tests for China's national CPI remain scarce [16].

This paper addresses these gaps by (1) applying the Box-Jenkins methodology to China's monthly CPI, (2) explicitly comparing the out-of-sample forecasting accuracy of SARIMA against non-seasonal ARIMA over a 24-month holdout period, and (3) providing a quantitative baseline for near-term inflation trends.

3. Theoretical Models and Research Methods

3.1 Model Framework

This study follows the Box-Jenkins time series modeling methodology [13]. The general ARIMA(p,d,q) model is used to describe a univariate time series y_t that has been made stationary through dd-order differencing. Its mathematical form is given by:

where B is the backshift operator (i.e., $B=$), ϵ_t is a white noise process with zero mean and constant variance. The autoregressive (AR) polynomial is $\phi(B)$, and the moving average (MA) polynomial is $\theta(B)$. The model captures the linear dependency structure of the series using p autoregressive and q moving average terms.

To account for the inherent annual seasonality in monthly data, the Seasonal ARIMA model-SARIMA(p,d,q)(P,D,Q)_s is employed. This model extends the ARIMA framework by incorporating both non-seasonal and seasonal components. Its full specification can be written as:

where s denotes the number of periods per season (for monthly data, $s=12$). The seasonal AR polynomial $\Phi(B^s)$, and the seasonal MA polynomial $\Theta(B^s)$. The terms $\phi(B)$ and $\theta(B)$ represent the non-seasonal and seasonal differencing operators, respectively.

3.2 Modeling Procedure and Evaluation System

This study adheres to the complete four-stage Box-Jenkins process:

Stage 1: Stationarity Test and Seasonal Adjustment. The ADF unit root test is used to assess stationarity; seasonal decomposition and monthly mean analysis determine seasonal patterns.

Stage 2: Model Identification. ACF and PACF plots provide preliminary order estimates. A grid search over candidate orders selects the model with minimum Akaike Information Criterion (AIC).

Stage 3: Parameter Estimation and Diagnostic Checking. Maximum likelihood estimation is used for parameter estimation. Residual diagnostics include the Ljung-Box Q test for independence, ARCH-LM test for heteroskedasticity, and normality tests.

Stage 4: The dataset is split into training and test sets. Out-of-sample forecast accuracy is evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Mean Absolute Percentage Error (MAPE) is noted but used with caution when actual values approach zero.

Analysis

4.1 Data Sources and Sample Split

Monthly CPI year-on-year data from February 1996 to August 2025 (354 observations) is sourced from the National Bureau of Statistics of China. The sample is split into a training set (Feb 1996-Aug 2023, 330 obs) for modeling and a test set (Sep 2023- Aug 2025, 24 obs) for validation.

4.2 Descriptive Statistics

4. Data Selection and Preliminary



Fig. 1 Monthly CPI trend in China year-on-year (after cleaning)

Fig. 1 shows the monthly CPI trend. The series exhibits several landmark fluctuations: a decline from high levels after 1996; low or negative readings during 1998-2003; sharp rises in 2004 and 2007-2008; a brief negative dip in 2009; another surge in 2010-2011; and a gradual down-

ward trend since 2020, with low-level hovering since 2023. The test period falls within this low-inflation environment, making out-of-sample forecasting particularly challenging.

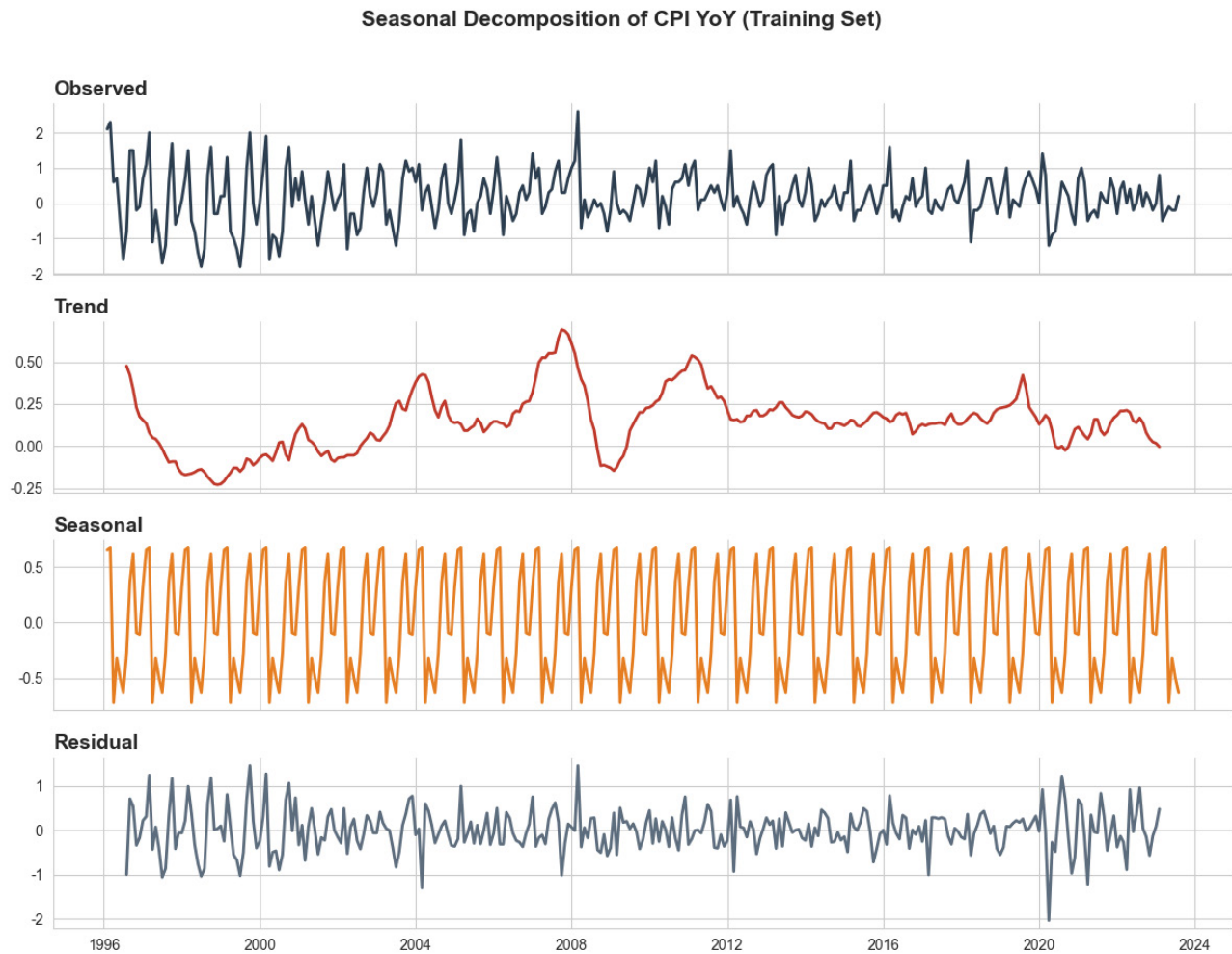


Fig. 2 Seasonal Decomposition of CPI YoY (Training Set)

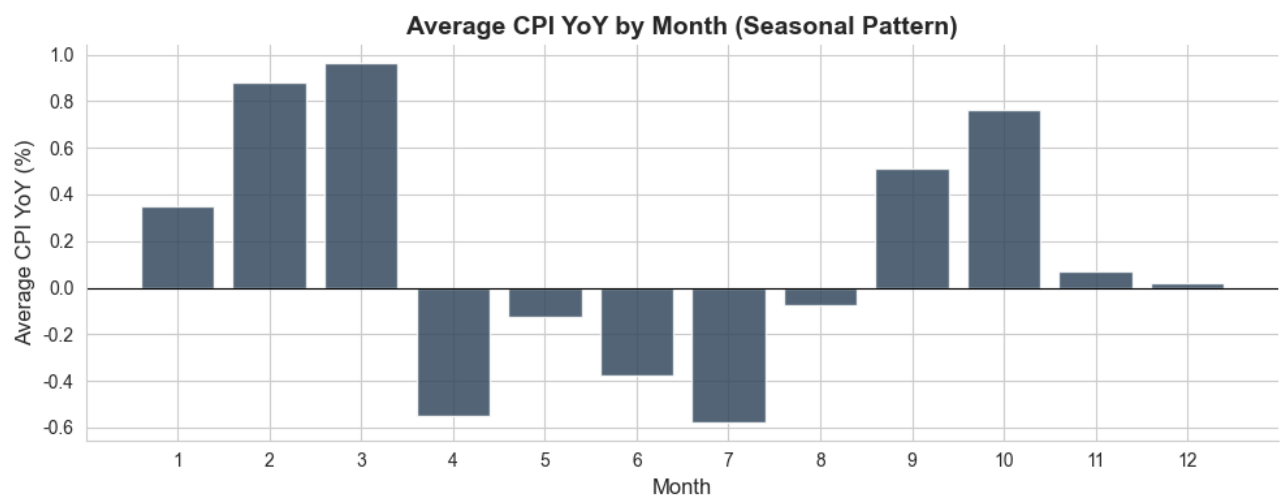


Fig. 3 Average CPI YoY by Month (Seasonal Pattern)

Seasonal decomposition (Fig. 2 and Fig. 3) reveals a regular intra-annual pattern: January and February (Spring Festival effect) show higher values, while summer months

are lower. This confirms that despite year-on-year calculations partially removing seasonal factors, the series retains a non-negligible annual cyclical pattern—providing direct

justification for employing the SARIMA model.

4.3 Stationarity Test of the Series

A prerequisite for building a SARIMA model is that the

series is stationary or can be made stationary through appropriate differencing. This study uses the ADF unit root test to assess the stationarity of the CPI year-on-year series in the training set. The test results are reported in Table 1.

Table 1. ADF Unit Root Test Results for CPI YoY Series

Item	Statistic/Critical Value
ADF Statistic	-3.8615
p-value	0.0023
1% Critical Value	-3.4515
5% Critical Value	-2.8708
10% Critical Value	-2.5717
Conclusion	Series is stationary; reject unit root null

As shown in Table 1, the ADF unit root test yields a statistic of -3.8615 ($p=0.0023$), with an absolute value exceeding the critical values at the 1%, 5%, and 10% significance levels. The null hypothesis of a unit root is strongly rejected, indicating that the CPI year-on-year series is stationary; thus, $d=0$. Furthermore, the ACF plot shows no extremely slow decay at lag 12, suggesting that $D=0$ is also appropriate, a judgment subsequently validated by the grid search.

5. SARIMA Model Establishment and

Diagnostics

Chapter 4 confirmed the stationarity of the CPI year-on-year series and revealed its inherent seasonal characteristics. Building on this foundation, this chapter systematically executes the Box-Jenkins modeling procedure outlined in Chapter 3 to complete the identification, estimation, and diagnostic checking of the SARIMA model. A non-seasonal ARIMA model is also constructed as a benchmark to test the necessity of incorporating seasonal terms.

5.1 SARIMA Model Identification and Order Selection

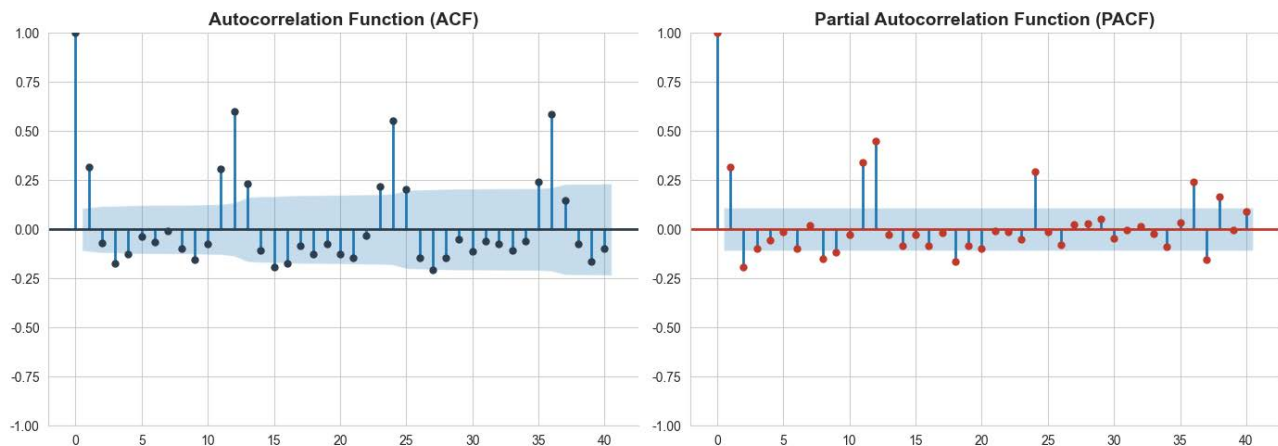


Fig. 4 ACF and PACF

With $d=0$, $D=0$, and $s=12$, ACF and PACF plots (Fig.4) inform preliminary order selection. The ACF shows significant positive correlation at lag 1 with rapid decay, but noticeable peaks at lags 12 and 24, confirming annual seasonality. The PACF shows a significant spike at lag 1 and another at lag 12. These features suggest low-order non-seasonal AR and MA terms and at least one seasonal

term.

A search over $p, q \in \{0, 1, 2\}$ and $P, Q \in \{0, 1\}$ identifies SARIMA(1,0,2)(1,0,1)₁₂ as optimal (AIC=386.19), the lowest among all candidates (Table 2). Models with both seasonal AR ($P=1$) and seasonal MA ($Q=1$) terms generally outperform those lacking seasonal components.

Table 2. AIC Comparison of Candidate SARIMA Models (Partial)

Model	AIC
(1,0,2)(1,0,1)	386.19
(2,0,1)(1,0,1)	387.45
(1,0,1)(1,0,1)	388.72
(2,0,2)(1,0,1)	388.90
(1,0,2)(0,0,1)	391.53
(1,0,2)(1,0,0)	393.10

5.2 Model Estimation Results

Table 3.

Maximum likelihood estimation results are summarized in

Table 3. Parameter Estimates for SARIMA(1,0,2)(1,0,1)₁₂ Model

Parameter	Estimate	Std. Error	z-statistic	p-value	95% Confidence Interval
ar.L1	0.7228	0.150	4.815	0.000	[0.429, 1.017]
ma.L1	-0.5848	0.161	-3.633	0.000	[-0.900, -0.269]
ma.L2	-0.0356	0.062	-0.575	0.565	[-0.157, 0.086]
ar.S.L12	0.9070	0.014	66.113	0.000	[0.880, 0.934]
ma.S.L12	-0.7383	0.046	-16.033	0.000	[-0.828, -0.648]
σ^2	0.1861	0.011	16.956	0.000	[0.165, 0.208]

The non-seasonal autoregressive term (ar.L1=0.7228) is highly significant, indicating strong short-term inertia. The seasonal terms (ar.S.L12=0.9070, ma.S.L12=-0.7383) are both highly significant, characterizing the annual memory and shock adjustment mechanisms of CPI.

5.3 Residual Diagnostics and Model Checking

5.3.1 Ljung-box White Noise Test

The Ljung-Box Q-test is performed on the residual series, with test statistics computed at lags 12, 24, and 36. The results are presented in Table 4.

Table 4. Ljung-Box White Noise Test Results for Residuals

Lag Order	Q-statistic	p-value
12	23.31	0.025
24	30.40	0.172
36	52.53	0.037

At the 5% significance level, the p-value at lag 24 is 0.172 (cannot reject white noise). P-values at lags 12 (0.025) and 36 (0.037) suggest weak residual correlation at isolat-

ed lags, but overall results are acceptable for macroeconomic time series modeling.

5.3.2 Residual Autocorrelation Plots

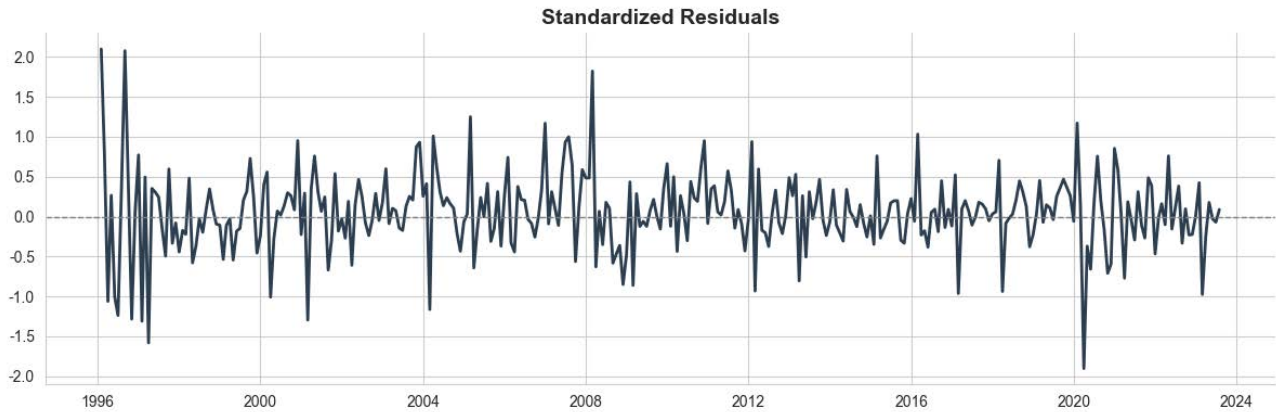


Fig. 5 Standardized Residuals

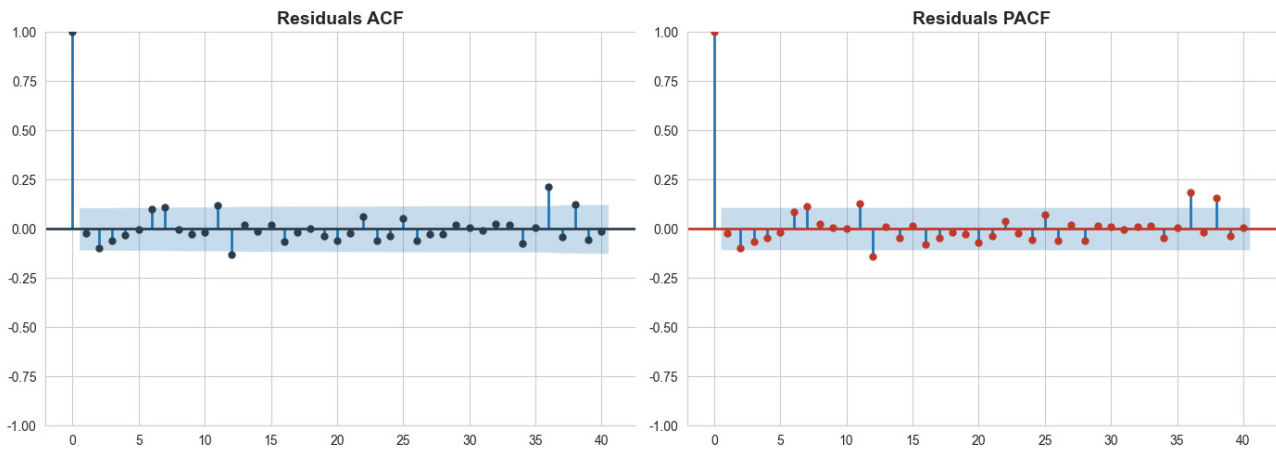


Fig. 6 Residuals ACF and PACF

Residuals fluctuate randomly around zero with no discernible trend or volatility clustering (Fig. 5 and Fig. 6). Almost all autocorrelation coefficients lie within the two-standard-error band. The ARCH-LM test yields a two-sided p-value of 0.86, ruling out immediate need for GARCH-type structures.

5.3.3 Normality Test

The Jarque-Bera statistic is 68.40 ($p \approx 0.00$), indicating non-normal residuals with slight negative skewness and fat tails. This does not affect coefficient consistency or asymptotic inference but implies forecast confidence intervals may be less precise under extreme scenarios. Overall, diagnostic results confirm that the SARIMA(1,0,2)(1,0,1)₁₂ model has essentially extracted the

linear dependence structure and seasonal pattern from the CPI year-on-year series. The residuals approximate white noise, and the model specification is deemed adequate and appropriate.

5.4 Model Stability and In-Sample Fit Performance

To quantify the improvement gained from incorporating seasonal terms, a non-seasonal ARIMA model is constructed as a benchmark. Using an automated order selection procedure on the training set, the optimal non-seasonal model is identified as ARIMA (2,0,1). The in-sample AIC and out-of-sample forecast accuracy for both models are compared in Table 5.

Table 5. Comparison of SARIMA and ARIMA Model Fit and In-Sample Metrics

Model	Non-SeasonalOrders	SeasonalOrders	AIC
SARIMA	(1, 0, 2)		386.19
ARIMA	(2, 0, 1)	-	395.47

A non-seasonal ARIMA(2,0,1) model is constructed as a benchmark (AIC=395.47 vs. 386.19 for SARIMA). The AIC reduction far exceeds the penalty for adding two seasonal parameters, supporting the necessity of seasonal modeling. However, in-sample fit alone does not guarantee predictive power-the true test lies in out-of-sample performance, which is the focus of Section 6.

6. Out-of-Sample Forecasting and

Trend Analysis

6.1 Out-of-Sample Forecast Accuracy Evaluation

Using August 2023 as the forecast origin, dynamic forecasts are generated for the subsequent 24 months, simulating a real-world scenario. Because several monthly CPI values in the test period are close to zero, MAPE is not reported; RMSE and MAE serve as primary metrics.

Table 6. Out-of-Sample Forecast Accuracy Comparison (24 Months, 2023.09-2025.08)

Model	RMSE	MAE
SARIMA (1,0,2)(1,0,1) ₁₂	0.384	0.296
ARIMA (2, 0, 1)	0.447	0.349

Table 6 clearly shows that the SARIMA model outperforms the non-seasonal ARIMA model on both metrics [14]. RMSE reduced by 14.1%, MAE by 15.2%. The average absolute forecast error is less than 0.3 percentage points, demonstrating remarkably high short-term accuracy. This directly answers the core research question: modeling seasonal effects significantly improves out-of-sample forecast accuracy, not just in-sample fit. The roughly 15% error reduction has considerable economic value for policymakers and market participants.

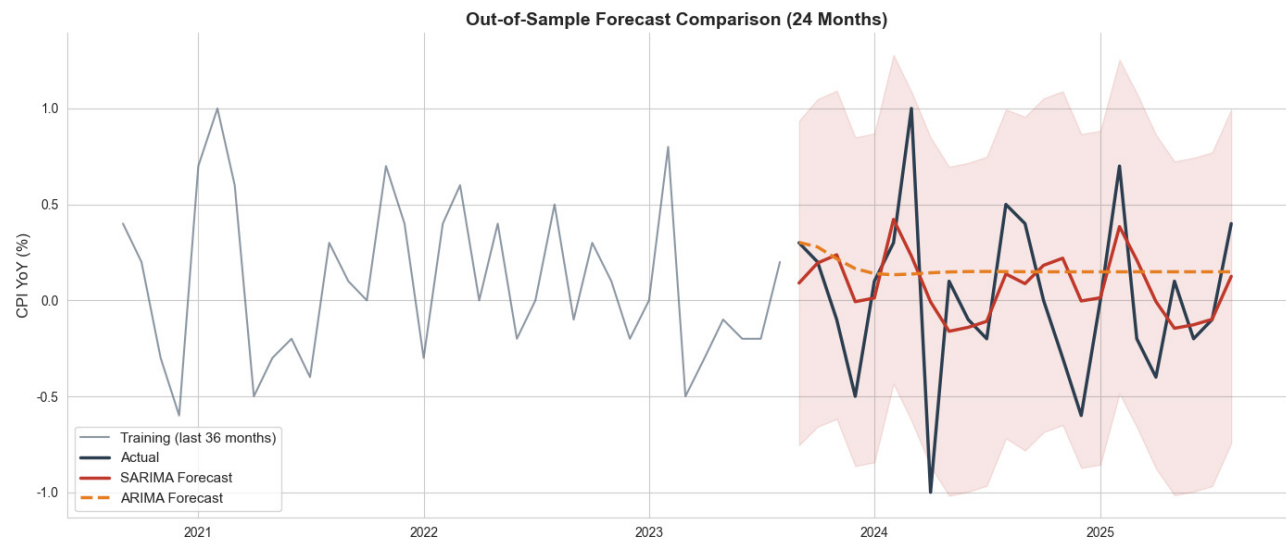


Fig. 7 Out-of-Sample Forecast Comparison (24 Months)

The Fig. 7 provides a more intuitive view: in the first 12 months of the test period, the two forecast curves show similar trajectories, both tracking the direction of the actual values reasonably well. However, the SARIMA forecast line consistently stays closer to the true values. In the latter 12 months, as the forecast horizon lengthens, the ARIMA's forecast errors gradually accumulate, while the SARIMA maintains a relatively stable tracking ability.

Its forecast confidence bands are also narrower, reflecting the contribution of the seasonal component to longer-term forecast stability.

6.2 12-Month Ahead CPI Forecast Path

Using the validated SARIMA (1,0,2)(1,0,1)₁₂ model, forecasts for the next 12 months (September 2025 to August 2026) are generated (Fig. 8).

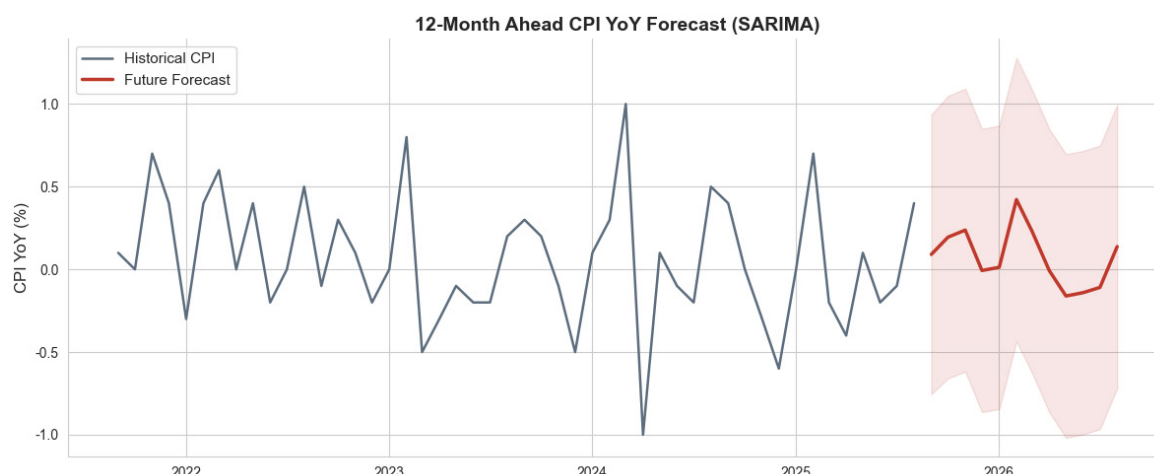


Fig. 8 12-Month Ahead CPI YoY Forecast (SARIMA)

The forecast indicates that China's CPI will maintain a moderate upward trend, stabilizing in the 1.0%-1.5% range by the first half of 2026, up from an initial 0.5%. Although seasonal factors may cause temporary fluctuations, the overall upward shift in the central tendency remains gentle. The 95% confidence intervals remain entirely positive, indicating high confidence that sustained deflation will not occur. This trajectory aligns with current economic fundamentals—characterized by steady but not robust demand, a mild pork cycle, lower commodity prices, and accommodative monetary policy—reflecting a slow normalization under low-inflation conditions.

6.3 Discussion of the Inflation Trend

The 12-month-ahead forecast depicts a scenario of "low-level recovery" for China's CPI inflation.

Structural context. The modest rebound reflects a demand recovery that, since 2023, has been steady but not robust—goods consumption and household willingness to spend have recovered slowly, while the real estate adjustment continues to suppress housing-related prices. The gradual upward trend captured by the model aligns with Gu's finding that the Phillips Curve trade-off remains muted in China due to labor market segmentation and employment-first policies, explaining why even economic normalization does not generate strong demand-pull inflation [17].

Seasonal volatility. The model's strong seasonal parameter ($\text{ar.S.L12} = 0.907$) indicates that the annual cycle is the primary source of short-term fluctuations. Spring Festival effects, summer travel peaks, and year-end carryover may temporarily push CPI by 0.2-0.5 percentage points in certain months. Policy evaluation must distinguish these seasonal movements from genuine trend changes.

Low-inflation risks and international comparison. Even by mid-2026, the average CPI rate will remain below historical averages and below levels generally preferred for

monetary policy. Persistently low inflation implies higher real interest rates, potentially dampening investment and consumption. Notably, while Yao found SARIMA performed better on U.S. PPI than CPI, the results indicate that for China, incorporating seasonality is the decisive accuracy factor—suggesting China's CPI is more sensitive to seasonal consumption patterns (particularly holiday effects) than its U.S. counterpart [11].

Model choice. While Luo and Ding demonstrated LSTM's superiority over ARIMA for regional CPI, the findings of this study suggest that for national-level data, linear SARIMA remains highly effective and parsimonious [16]. The regularity of seasonal patterns makes deep learning prone to overfitting with limited marginal gains, while SARIMA's interpretability is valuable for policy applications.

Caveats. The forecast assumes no structural breaks; major policy shifts, external shocks, or supply disruptions could cause deviations. This baseline should be complemented with structural models, survey-based expectations, and professional judgment. Future work could incorporate leading indicators such as the Financial Condition Index into a SARIMAX framework to better capture financial transmission channels [18].

7. Conclusion

This study addresses four research questions and summarizes the following key findings.

Time series characteristics: Since 1996, China's CPI year-on-year growth has experienced multiple pronounced fluctuation cycles, including periods of both inflationary pressure and disinflation. Over time, the central tendency has gradually shifted downward, accompanied by a narrowing range of volatility. Seasonal decomposition confirms the existence of a non-negligible annual cyclical pattern, reflecting the influence of recurring consumption behaviors

and seasonal economic activities. The ADF test rejects the null hypothesis of non-stationarity at the 1% significance level, providing a reliable statistical foundation for SARIMA (p,0,q)(P,0,Q)₁₂ modeling.

Model identification: The optimal specification is identified as SARIMA (1,0,2)(1,0,1)₁₂ based on the minimum AIC value (386.19). Both non-seasonal and seasonal components are statistically significant, indicating that the model successfully captures both short-term dynamics and recurring seasonal movements. Residual diagnostic tests confirm that the model has adequately extracted the major linear and seasonal patterns. Although residual non-normality is observed, it does not materially undermine the forecasting performance or validity of the model.

Forecasting advantage: Using a 24-month test set, SARIMA achieves RMSE of 0.384 and MAE of 0.296, representing reductions of 14.1% and 15.2%, respectively, compared with ARIMA (2,0,1). These results provide clear empirical evidence that explicitly incorporating seasonal effects significantly improves CPI forecasting accuracy.

Future trajectory: The 12-month-ahead forecast suggests a moderate upward trend, with CPI growth increasing from approximately 0.5% toward the 1.0%-1.5% range by mid-2026. The forecast does not indicate a sustained deflation risk, while also suggesting limited momentum for rapid price increases. Overall inflationary pressure remains manageable, although persistently low inflation requires continued policy attention.

Policy implications and limitations: Monetary policy should remain prudent and accommodative to support economic recovery. While time-series forecasts provide a quantitative reference, policymakers should remain alert to the risks associated with prolonged low inflation and potentially anchored deflationary expectations. Distinguishing seasonal fluctuations from underlying inflation trends is essential for effective policy design. This study has two main limitations. First, SARIMA assumes linear relationships, whereas economic systems may exhibit complex nonlinear dynamics. Although the findings demonstrate that linear SARIMA performs well for national-level CPI, future research could investigate hybrid approaches (SARIMA-LSTM) or advanced architectures (Transformer, Autoformer) to capture nonlinear shocks. Second, the model assumes parameter stability; future studies could incorporate structural break tests to address regime shifts caused by major policy changes or global events, and extend the univariate framework through multivariate models such as SARIMAX.

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