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An Empirical Study on USD/CNY Exchange Rate Based on the ARIMA Model

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Abstract

This paper analyzes the monthly average USD/CNY exchange rate data from June 2006 to June 2025 using time series methods, with a total of 229 samples. The EViews software is employed to construct an ARIMA model for this time series. The model accuracy is tested using data from July 2023 to June 2025, and the USD/CNY exchange rate is forecasted for the next two years.

Keywords

ARIMA Model, RMB Exchange Rate, Forecasting

1. Introduction

The exchange rate is a core variable in international economic and financial transactions, exerting a significant impact on international trade, capital flows, and financial markets. Since the reform of the RMB exchange rate formation mechanism, the volatility characteristics of the USD/CNY exchange rate have changed notably. Relying on its global and round-the-clock advantages, the foreign exchange market has become the world's largest financial market in terms of trading volume. Since 2010, China's foreign exchange market has undergone multiple rounds of exchange rate policy adjustments and been affected by various external shocks, including the global financial crisis, Sino-US trade frictions, the COVID-19 pandemic, and the Russia-Ukraine conflict. Xie Jianguo *et al.*, (2019) [1] divided the sample period into pre- and post-"811 Exchange Rate Reform" phases and conducted a comparative empirical study on the impacts on the USD/CNY exchange rate before and after the reform. Wang Panpan (2021) [2] used the GARCH model and found that the mean spillover effect of US economic policy uncertainty on the RMB exchange rate disappeared after the "811 Exchange Rate Reform", while the volatility spillover effect intensified during the Sino-US trade frictions. Liu Qiang *et al.*, (2022) [3] applied the TVP-VAR model and revealed that the spillover of short-term capital flows on the RMB exchange rate gradually emerged with the deepening of market-oriented reforms. Similarly, Deng Daocai *et al.*, (2019) [4] investigated the spillover effects of Fed policy shifts on emerging economies including China, and the empirical results showed structural changes in the impact of Fed interest rate hikes on the exchange rates of the BRICS countries. On August 11, 2015, the People's Bank of China announced further improvements to the market-oriented reform of the RMB exchange rate formation mechanism, adjusting the mechanism based on market supply and demand and the previous central parity rate. This policy increased the depreciation pressure on the RMB in the short run [5]. COVID-19 triggered global market volatility and also affected China's foreign exchange market. However, thanks to the timely and proactive measures taken by the Chinese government, the economy recovered significantly [6].

This paper analyzes monthly average exchange rate data from June 2006 to June 2025 using time series methods. The monthly average exchange rate is calculated as the unweighted average of all available daily USD/CNY onshore spot rates in the corresponding month. Missing values, if any, are linearly interpolated prior to averaging, yielding a total of 229 samples. The data were obtained from the Wind database. EViews is used to analyze the time series [7] [8], establish the ARIMA model, test the model accuracy with data from July 2023 to June 2025, and forecast the USD/CNY exchange rate for the next two years. First, descriptive statistics and visual analysis are adopted to reveal data characteristics. Second, the ADF test is used to examine stationarity. Then, ARIMA model identification and order determination are completed based on ACF/PACF analysis and information criterion comparison. Next, parameter estimation is performed using the least squares method, and model adequacy is verified through residual white noise test and normality test. Finally, out-of-sample forecasting is conducted, and evaluation indicators such as MSE and MAE are calculated. The results show that the ARIMA (3, 1, 2) model can effectively fit the volatility of the USD/CNY exchange rate.

2. Data Preprocessing (Descriptive Statistics)

First, descriptive statistical analysis is carried out by calculating statistics including the mean, median, and standard deviation to understand the central tendency, dispersion, and volatility of the data. Meanwhile, indicators such as skewness and kurtosis reveal the distribution shape of the data, and normality tests help determine whether the data conform to specific statistical distribution assumptions. This information not only helps identify potential data problems but also lays the foundation for selecting appropriate subsequent analysis methods, constructing effective forecasting models, and interpreting model results, ensuring the rationality of the analysis process and the reliability of the outcomes. As shown In **Figure 1**:

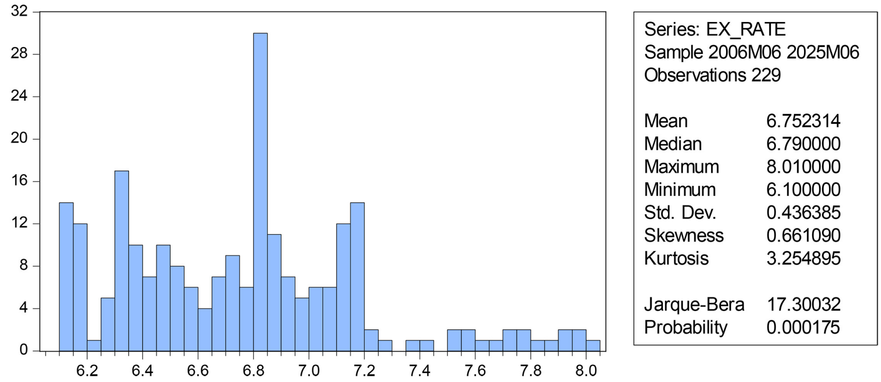


Figure 1. Descriptive statistics.

According to the analysis results, the mean value of the exchange rate time series is 6.752314 and the median is 6.790000. The median is slightly higher than the mean, indicating that the data present a weak positive skewed distribution. The maximum and minimum values of the data are 8.01 and 0.43 respectively, with a standard deviation of 0.661090, showing that the exchange rate experienced a wide fluctuation range during the observation period, but the overall volatility was relatively controllable. The skewness coefficient of 0.463585 further confirms a slight positive skewness, while the kurtosis coefficient of 3.254895 is close to 3, suggesting a relatively gentle distribution shape. The p-value of the Jarque-Bera normality test is much smaller than 0.05, which clearly rejects the null hypothesis that the data follow a normal distribution.

3. Stationarity Test

3.1. ADF Test

The ADF test is performed when constructing the ARIMA model mainly to determine whether the time series is stationary. Since the ARIMA model is based on the assumption of data stationarity, non-stationary data will lead to inaccurate parameter estimation of the model.

It can be seen from the time series plot in **Figure 1** that the data from June 2006 to June 2025 show obvious fluctuations and represent a non-stationary series, indicating that the data are affected by various factors, resulting in different patterns in different periods.

Table 1. Results of the ADF test.

Test Form	t-statistic	p-value	1% critical value	Test Result
With trend and intercept	−2.694664	0.2399	−3.998997	Non-stationary
With intercept only	−2.809152	0.0585	−3.459101	Non-stationary
No trend, no intercept	−0.700247	0.4126	−2.575189	Non-stationary

As shown in **Table 1**, the results consistently indicate that the time series is non-stationary, regardless of whether the test specification includes trend and intercept, intercept only, or neither trend nor intercept. At the 1% significance level, the absolute values of the t-statistics are all lower than the corresponding critical values, and the p-values are all greater than the significance level. Therefore, the null hypothesis of the existence of a unit root cannot be rejected. Further differencing of the data is required before conducting subsequent time series modeling and analysis.

3.2. Differencing Processing

Based on the ADF test, it is confirmed that differencing must be applied to the data to eliminate trend and non-stationarity so that the series meets the modeling requirements of the ARIMA model.

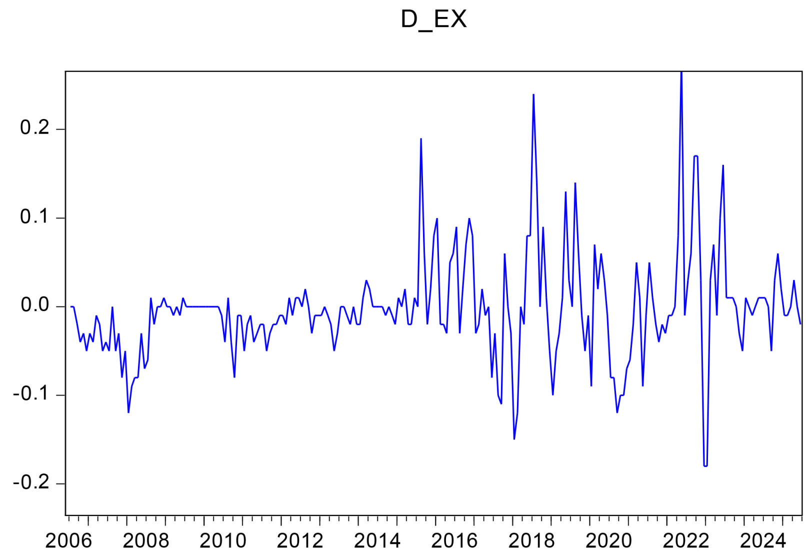


Figure 2. Time series plot after first-order difference.

As shown in **Figure 2**, the series after first-order differencing does not exhibit a continuous upward or downward trend during the observation period, but fluctuates around a relatively stable level. Its short-term rises and falls do not deviate from the central value, indicating that the first-order differenced series is stationary-order differenced series is stationary.

Table 2. ADF test results after first-order differencing.

Test Form	t-statistic	p-value	% critical value	Test Result
With trend and intercept	−9.080593	0.0000	−3.998997	Stationary
With intercept only	−8.819263	0.0000	−3.459101	Stationary
No trend, no intercept	−8.817749	0.0000	−2.575189	Stationary

As shown in **Table 2**, regardless of whether the test form includes trend and intercept, intercept only, or neither trend nor intercept, the absolute values of the t-statistics are significantly higher than the critical values at the corresponding significance levels, and the corresponding p-values are all much smaller than 0.01. These results indicate that we can reject the null hypothesis of the existence of a unit root, and thus conclude that the series after first-order differencing is stationary.

4. Model Identification and Order Determination

4.1. ACF/PACF Analysis

Autocorrelation and partial autocorrelation are key diagnostic tools prior to time series modeling. Using the autocorrelation function and partial autocorrelation function, the dependence structure, trends, or seasonal patterns in the data can be identified, which helps in selecting an appropriate model. The Q-statistic and its corresponding p-value are used to test the overall significance of autocorrelation and determine whether the time series has a modelable dynamic structure.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.486	0.486	54.540	0.000
		2	0.160	-0.100	60.450	0.000
		3	0.077	0.053	61.827	0.000
		4	0.092	0.059	63.794	0.000
		5	0.052	-0.027	64.425	0.000
		6	-0.049	-0.087	64.983	0.000
		7	-0.070	-0.007	66.144	0.000
		8	-0.070	-0.039	67.306	0.000
		9	0.080	0.173	68.851	0.000
		10	0.186	0.113	77.160	0.000
		11	0.087	-0.078	78.988	0.000
		12	0.093	0.109	81.076	0.000
		13	0.087	-0.020	82.915	0.000
		14	0.006	-0.110	82.923	0.000
		15	-0.061	-0.025	83.851	0.000
		16	-0.069	-0.004	85.028	0.000
		17	-0.082	-0.046	86.707	0.000
		18	-0.087	0.009	88.614	0.000
		19	-0.023	0.024	88.746	0.000
		20	-0.034	-0.066	89.045	0.000
		21	-0.018	0.035	89.129	0.000
		22	-0.022	-0.082	89.255	0.000
		23	-0.037	-0.039	89.608	0.000
		24	-0.106	-0.074	92.494	0.000

Figure 3. Results of autocorrelation and partial autocorrelation.

As shown in **Figure 3**, the time series exhibits significant autocorrelation and a dynamic structure. The autocorrelation coefficient at lag 1 is relatively high, indicating strong short-term dependence. As the lag order increases, the AC values gradually decrease but still show significant peaks near lags 10 and 12, implying potential long-term dependence. The partial autocorrelation decays rapidly after lag 1, but rebounds at some higher lags including lags 9, 10, and 12, suggesting that the data may contain both autoregressive and moving average components. The p-values of the Q-test for all lags are 0.000, rejecting the null hypothesis of "no autocorrelation" and indicating that the series has a significant autocorrelation pattern. Therefore, the time series is suitable for modeling with the ARIMA model to capture its short-term dynamics and underlying characteristics. Analysis Based on the above analysis, a preliminary model cannot be determined. Therefore, several models are selected for comparison: ARIMA (2, 1, 0), ARIMA (1, 1, 1), ARIMA (2, 1, 1), ARIMA (1, 1, 2), ARIMA (3, 1, 2), and ARIMA (3, 1, 1).

4.2. Model Comparison

The core role of model comparison is to select the model that best fits the data characteristics while possessing both explanatory power and parsimony from multiple candidate models through systematic evaluation. By comparing the statistical indicators of different ARIMA structures, overfitting can be effectively avoided, model robustness verified, and model deficiencies diagnosed, so as to ensure that the finally selected model achieves an optimal balance between statistical rigor and predictive practicality. Based on the preliminarily determined models above, model comparisons are conducted as shown in **Table 3**:

Table 3. Model comparison results.

Model	Significant Coefficients	AIC	BIC	Convergence Iterations	DW Statistic	R-squared
ARIMA (2, 1, 0)	AR (1)	−2.988	−2.923	4	1.967	0.253
ARIMA (1, 1, 1)	AR (1)	−2.989	−2.924	7	1.975	0.253
ARIMA (2, 1, 1)	None	−2.979	−2.898	15	1.975	0.253
ARIMA (1, 1, 2)	None	−2.98	−2.898	19	1.977	0.254
ARIMA (3, 1, 2)	All AR/MA terms	−2.996	−2.882	40	1.983	0.283
ARIMA (3, 1, 1)	None	−2.972	−2.874	18	1.982	0.255

Through a systematic evaluation of all candidate models, the ARIMA (3, 1, 2) model performs the best and is selected as the optimal one. This model not only has the highest explanatory power, with an R-squared value of 0.283 that is significantly better than other models, but also all its autoregressive and moving average terms are statistically significant, ensuring the reliability of the model. Although the model is relatively complex and requires 40 iterations to converge, its lowest AIC value and Durbin-Watson statistic close to 2 demonstrate that it achieves an optimal configuration in balancing model complexity and prediction accuracy. In contrast, other models either lack explanatory power or suffer from insignificant parameters. Therefore, the overall advantages of the ARIMA (3, 1, 2) model in prediction accuracy and statistical reliability make it the best choice for the exchange rate forecasting task.

4.3. Residual Diagnosis

Residual testing plays a critical role in time series modeling. Qualified residual test results not only validate the effectiveness of model assumptions but also ensure the reliability of prediction intervals, serving as an important basis for evaluating model quality and guiding model improvement. Only when the residuals pass all relevant tests can the model be considered to have maximally extracted the predictable information from the data. To verify whether the ARIMA (3, 1, 2) model is appropriate for the time series of the USD to CNY exchange rate, residual tests are conducted.

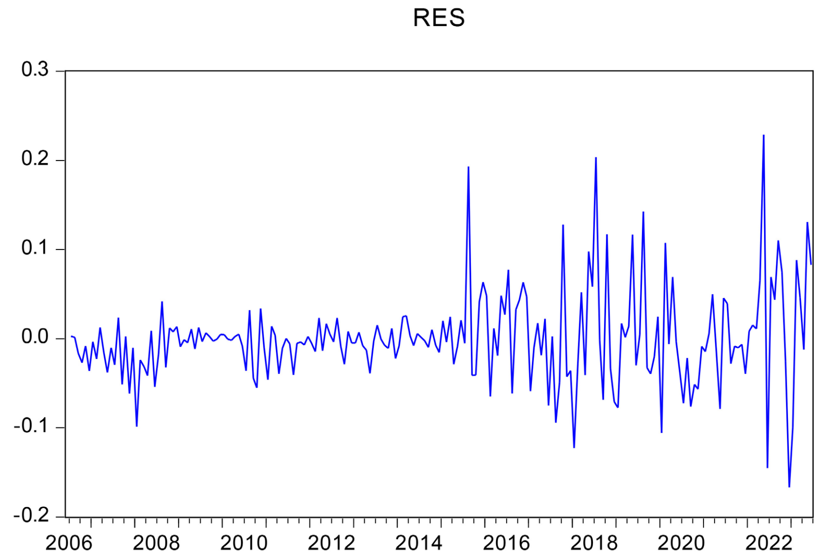
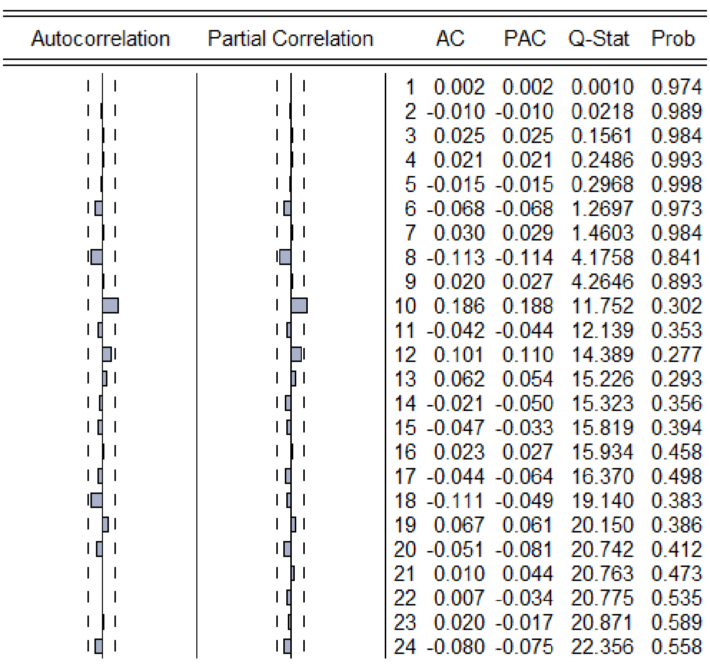


Figure 4. Residual time series plot.

As shown in **Figure 4**, the data fluctuates steadily around zero, with the fluctuation range basically stable between −2 and +3. No obvious trend, periodicity, or heteroscedasticity is observed, indicating that the model has well captured the main dynamics of the data. Overall, the residual series exhibits favorable randomness and conforms to the basic assumption of white noise, suggesting that the model specification is generally reasonable.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0010	0.974
		2	-0.010	-0.010	0.0218	0.989
		3	0.025	0.025	0.1561	0.984
		4	0.021	0.021	0.2486	0.993
		5	-0.015	-0.015	0.2968	0.998
		6	-0.068	-0.068	1.2697	0.973
		7	0.030	0.029	1.4603	0.984
		8	-0.113	-0.114	4.1758	0.841
		9	0.020	0.027	4.2646	0.893
		10	0.186	0.188	11.752	0.302
		11	-0.042	-0.044	12.139	0.353
		12	0.101	0.110	14.389	0.277
		13	0.062	0.054	15.226	0.293
		14	-0.021	-0.050	15.323	0.356
		15	-0.047	-0.033	15.819	0.394
		16	0.023	0.027	15.934	0.458
		17	-0.044	-0.064	16.370	0.498
		18	-0.111	-0.049	19.140	0.383
		19	0.067	0.061	20.150	0.386
		20	-0.051	-0.081	20.742	0.412
		21	0.010	0.044	20.763	0.473
		22	0.007	-0.034	20.775	0.535
		23	0.020	-0.017	20.871	0.589
		24	-0.080	-0.075	22.356	0.558

Figure 5. Results of residual autocorrelation and partial autocorrelation analysis.

As shown in Figure 5, the autocorrelation of the series is weak. The absolute values of the autocorrelation coefficients and partial autocorrelation coefficients at various lag orders remain mostly below 0.2, with relatively high values appearing only at a few lag periods. The correlation coefficients for most lags are close to zero, indicating no significant autocorrelation in the series. Statistical significance tests show that the p-values of the Q-statistic at all lag periods are significantly greater than 0.05, so the null hypothesis that "the residuals are white noise" cannot be rejected. This indicates that the model has sufficiently extracted the autocorrelation information from the series. Overall, the residual series basically satisfies the white noise assumption, and the ARIMA (3, 1, 2) model has fully extracted the predictable information from the data. The model selection criterion based on information criteria and residual diagnostics ensures the reproducibility of the selection of the ARIMA (3, 1, 2) model.

5. Parameter Estimation

Parameter estimation plays a decisive role in time series modeling. By quantifying the coefficients of autoregressive (AR) and moving average (MA) terms, it reveals the extent to which historical observations and error terms affect the current value. It not only verifies the rationality of the model specification but also provides an accurate mathematical basis for subsequent forecasting, ensuring that the model can reliably capture the dynamic characteristics in the data. Therefore, the optimal model ARIMA (3, 1, 2) is selected for parameter estimation, as shown in Table 4:

Table 4. Parameter estimation of the ARIMA (3, 1, 2) model.

Parameter	Estimate	Std. Error	t-value	p-value
C	−0.00314	0.008421	−0.3729	0.7096
AR (3)	0.487529	0.061426	7.936837	0
AR (2)	−1.15212	0.065353	−17.6291	0
AR (1)	0.857794	0.073768	11.62826	0
MA (2)	0.922161	0.056714	16.25974	0
MA (1)	−0.30811	0.070885	−4.34658	0
SIGMASQ	0.002718	0.000179	15.21081	0

According to the parameter estimation results, the constant term coefficient of the model is −0.00314, with a p-value of 0.7096, which is not statistically significant, indicating that the influence of the constant term on the model is negligible. Among the autoregressive terms, the coefficients of AR (1), AR (2), and AR (3) are 0.857794, −1.152115, and 0.487529 respectively, and their p-values are all approximately 0, indicating high significance. This shows that the time series values of the past three periods have a significant impact on the current period value. In the moving average terms, the coefficients of MA (1) and MA (2) are −0.308106 and 0.922161 respectively, which are also highly significant, suggesting that recent random shocks exert a significant effect on the current value. In addition, the coefficient of the variance term is 0.002718, which is also highly significant, indicating that the residual variance of the model exhibits notable characteristics.

6. Model Forecasting

6.1. In-Sample Fitting

As a reliable tool, the forecasting model can improve the ability of market participants to respond to future exchange rate changes by capturing the subtle fluctuations and main trends of actual exchange rate data. Based on the ARIMA (3, 1, 2) model fitted above, the data from June 2023 to June 2025 were fitted to generate the fitting graph.

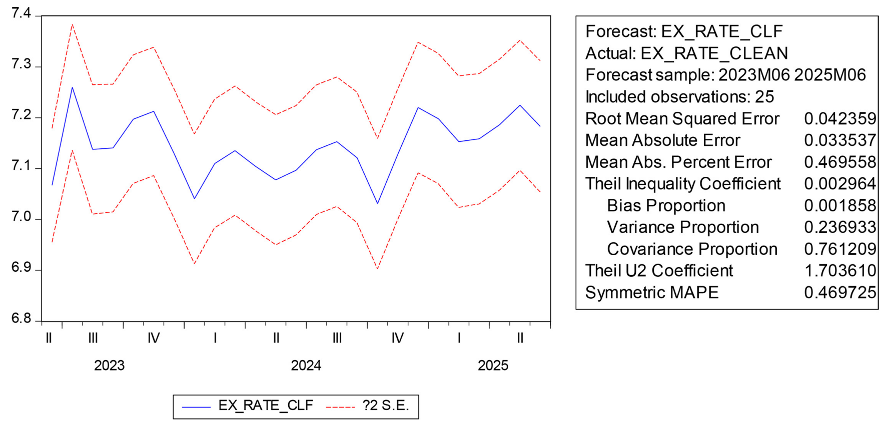


Figure 6. In-sample model prediction plot.

Table 5. In-sample fitting results.

Time	Forecast Value	Actual Value	Time	Forecast Value	Actual Value
2023-06	7.0671	7.15	2024-07	7.1371	7.13
2023-07	7.2598	7.16	2024-08	7.1529	7.13
2023-08	7.1376	7.17	2024-09	7.1213	7.08
2023-09	7.1405	7.18	2024-10	7.0311	7.11
2023-10	7.1971	7.18	2024-11	7.1284	7.17
2023-11	7.2125	7.15	2024-12	7.2199	7.19
2023-12	7.1301	7.1	2025-01	7.1977	7.18
2024-01	7.0408	7.11	2025-02	7.1530	7.17
2024-02	7.1099	7.11	2025-03	7.1586	7.17
2024-03	7.1354	7.1	2025-04	7.1863	7.2
2024-04	7.1047	7.1	2025-05	7.2247	7.2
2024-05	7.0778	7.11	2025-06	7.1831	7.18
2024-06	7.0969	7.12			

As shown in **Figure 6**, the predicted values are relatively close to the actual values at most time points, indicating a good fitting effect. Among them, the MAE and MAPE values are low, suggesting small prediction errors. The Theil inequality coefficient is close to 0, indicating a slight difference between predictions and actual values. The extremely low bias proportion implies no obvious systematic overestimation or underestimation in the forecasts. Meanwhile, the high variance proportion and covariance proportion demonstrate that the model can effectively capture the volatility of the actual data and maintain high consistency with it. Therefore, the prediction model exhibits high accuracy and reliability in exchange rate forecasting. The fitting results are shown in **Table 5**.

6.2. Dynamic Forecasting

Dynamic forecasting actively adjusts model parameters to adapt to system changes by continuously integrating real-time data and historical information, significantly improving prediction accuracy and timeliness. Its core value lies in capturing trend fluctuations, warning of potential risks, and supporting dynamic decision optimization. It can reduce biases caused by sudden environmental changes in static models, achieve the transformation from passive response to active intervention, and ultimately enhance the adaptability and competitiveness of the system.

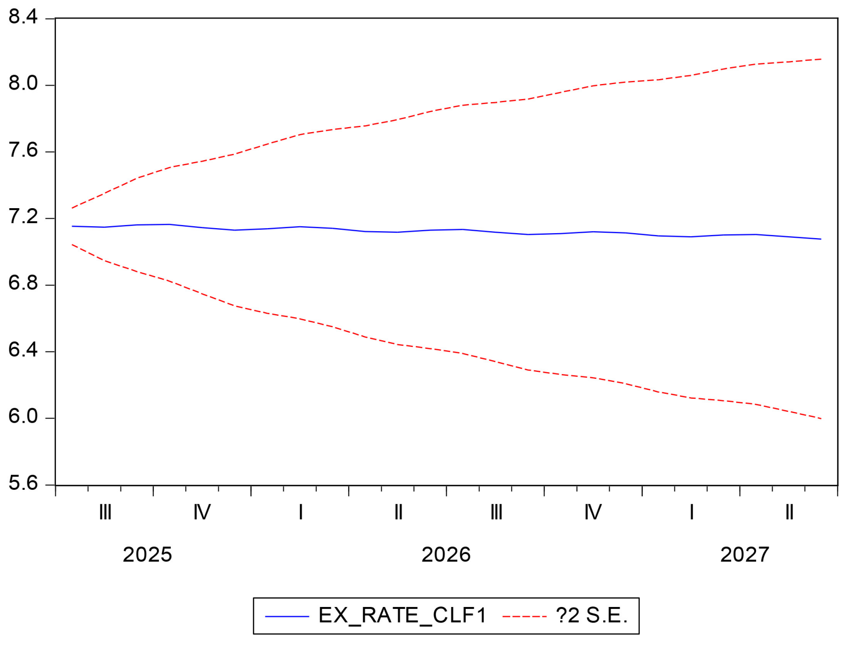


Figure 7. Future model prediction plot.

As shown in **Figure 7**, the predicted quarterly exchange rate values gradually decline from 8.4 to around 5.6, indicating that the exchange rate may exhibit a downward or fluctuating trend in the coming years. **Table 6** presents the forecast of the USD to CNY exchange rate for the next two years.

Table 6. Dynamic forecast.

Time	Forecast Value	Time	Forecast Value
2025-07	7.1532	2026-07	7.1342
2025-08	7.1478	2026-08	7.1178
2025-09	7.1618	2026-09	7.1035
2025-10	7.1644	2026-10	7.1092
2025-11	7.1453	2026-11	7.1202
2025-12	7.1303	2026-12	7.1134
2026-01	7.1380	2027-01	7.0953
2026-02	7.1502	2027-02	7.0903
2026-03	7.1419	2027-03	7.1011
2026-04	7.1219	2027-04	7.1047
2026-05	7.1178	2027-05	7.0904
2026-06	7.1307	2027-06	7.0767

7. Conclusions and Recommendations

This study constructs an ARIMA (3, 1, 2) model through time series analysis based on monthly USD to CNY exchange rate data from June 2006 to June 2025. The study finds that although the original data exhibit non-normal distribution and non-stationarity, they become stationary after first-order differencing, meeting the modeling requirements. No extreme outliers are detected in the outlier test, and the robustness of the model is further improved through truncation processing. The ARIMA (3, 1, 2) model performs best in the comparison; its significant autoregressive and moving average terms indicate that exchange rate fluctuations feature short-term memory and error correction effects, and residual tests verify the adaptability of the model. The model prediction results show that the in-sample fitted predicted values are highly consistent with the actual values, indicating that the model can effectively capture the main dynamic characteristics of the exchange rate. Dynamic forecasting suggests that the exchange rate will fluctuate narrowly around the range of 7.10 - 7.20 in the next two years without showing a significant trend change. This result provides an important decision-making reference for enterprises and investors. In addition, at the enterprise level, it is recommended that import and export enterprises adopt differentiated exchange rate risk management strategies: export enterprises may lock in forward contracts when the exchange rate approaches above the upper limit of 7.15 of the predicted range to avoid downside exchange rate risks; import enterprises should purchase foreign exchange opportunistically when the exchange rate approaches below the lower limit of 7.10 to reduce procurement costs. For policy-making authorities, it is recommended to establish a multi-level exchange rate monitoring and response mechanism. Regulators should take the predicted range of 7.10 - 7.20 as a benchmark reference and build a dynamic monitoring system. When the market exchange rate deviates continuously from this range, timely assessment should be made regarding unexpected policy adjustments or external shocks, and intervention measures should be adopted if necessary. These recommendations have three prominent features: first, strong operability, providing specific numerical range guidance; second, emphasis on differentiated strategies, designing customized schemes for different market entities; third, focus on dynamic optimization, including both a continuous monitoring mechanism and regular model updates.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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