Forecasting the RMB/USD Exchange Rate Using an ARIMA Model: Evidence from 2015 to 2025

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Abstract. This research applies an ARIMA (2,0,0) model to examine and predict the monthly RMB/USD exchange rate trends over the period from April 2015 to April 2025, aiming to explore how fluctuations in the exchange rate influence China's monetary strategies and international trade decision-making. The raw daily data are first integrated into monthly frequencies and processed through unit root tests and smoothing to ensure that the series meet the modeling requirements. The model selection process takes into account the goodness-of-fit and complexity, and ARIMA (2,0,0) is finally identified as the optimal solution, and the data from 2015 to 2022 are used as the training set, and 2023 to 2025 are used as the test set. The residual diagnostics show that the model error is consistent with white noise characteristics, and the Ljung-Box test shows no significant autocorrelation, indicating a reasonable fit. In the out-of-sample forecasts, the average absolute percentage error of the model is 7.53%, showing a moderate level of forecasting accuracy. Despite the slight underestimation of the upward trend of the exchange rate after 2022, the overall forecasting ability is still of practical value.

1 Introduction

The fluctuation of the RMB exchange rate is three dimensions that directly affect the regulation of China's monetary policy, the settlement cost of international enterprises and the risk premium in the capital market, which has a systemic impact on China's economic and financial system. Since China's major monetary reform on August 11, 2015, which changed the calculation of the RMB exchange rate in a more market-oriented direction, the conversion of the RMB to the U.S. dollar has entered a new phase of managed float, with a wider fluctuation band and higher forecasting difficulty. Accurate and interpretable exchange rate tools have become an important demand for relevant departments, commercial banks, and imports and exports. During the pre-reform period of 2012–2015, the central parity rate gradually increased its pricing influence over both onshore and offshore markets, and after the reform, the central rate further consolidated its role as a benchmark under the market-based regime [1].

Some of the current research methods are machine learning and deep learning nonlinear models, such as LSTM, CNN, etc.; the other category is the traditional linear time series models, such as ARIMA, GARCH, etc. Despite the advantages of nonlinear models in

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dealing with complex data structures, there are still some aspects that can limit the interpretability of the models and their application in policy making. For example, yet there are still insufficient studies on whether linear ARIMA models at the monthly level still provide stable and acceptable forecasting results at the monthly level with short samples and non-transparent parameters.

In order to fill the gap, the official daily data from April 2015 to April 2025 are selected in this paper. The optimal model is determined as ARIMA (2, 0, 0) by the auto.arima() function of R language, combined with the AIC and BIC criteria; the residual results show that the model error is white noise, there ACF plots reveal negligible autocorrelation, and the Ljung-Box test yields a p-value exceeding 0.05, which further verifies the reasonableness of the model fitting. The model is 7.53% on the test set of 2023-2025, which is not as low as the low error of the deep learning model, but still has the advantage of strong interpretability and low implementation cost without the need of big data and high computing power.

This paper aims to answer two questions: (1) Does the simplified ARIMA model provide acceptable short-term forecasting accuracy for RMB? (2) Can residual white noise diagnostics provide methodological credibility assessment for policy and practice sectors? The organization of this paper is as follows: Section 2 provides a literature review; Section 3 outlines the data sources and explains the model construction; Section 4 presents the empirical findings and comparative evaluations; Section 5 elaborates for future studies; the paper ends with a set of policy-oriented conclusions.

2 Literature Review

2.1 Existing Research Results

Linear time series modeling. Since Box and Jenkins proposed the ARIMA framework, this method has long been used as a benchmark model for exchange rate forecasting because of its simplicity of parameters, high interpretability, and low computational requirements. In the fifth edition of their work, state that ARIMA has a stable and controllable forecasting ability when the residuals are white noise [2]. An ARIMA (1, 1, 1) model to model the monthly exchange rate of RMB to USD and compare it with a simple exponential smoothing (SES) model. The results show that ARIMA exhibits lower root mean squared error (RMSE) and mean absolute deviation (MAE) for predictions within and beyond the training dataset, which is better than the random walk model, and verifies its stability and usefulness as a benchmark model for exchange rate forecasting [3]. Another study combined ARIMA with exponential smoothing for the forecasting of RMB exchange rate in COVID-19 period. achieved a monthly MAPE of less than 5% [4].

Regarding machine learning and deep learning approaches, one study compares the performance of ARIM with LSTM on 10 types of financial time series and find that the latter reduces the MAE by 80% [5]. Another study shows that with a longer training sample and the inclusion of macro variables, RNN significantly outperforms RNN. that RNN only significantly outperforms ARIMA and SVR [6]. A recent model, TS Mixer model that explains the role of the Transformer structure in RMB/USD exchange rate forecasting and visualizes the attention weights of the US dollar index on the RMB exchange rate [7].

2.2 Research Gaps

First, insufficient model interpretability: most neural network models are “black box structures” without white noise residual test and confidence interval output, which do not meet the requirements of financial regulation on risk control. Secondly, insufficient empirical

testing: there is no research specifically based on the monthly RMB/USD data from 2015M4 to 2025M4 to conduct systematic ARIMA model fitting, residual diagnosis and out-of-sample prediction error assessment.

2.3 Framework theory

In the framework of this paper is to draw on the structural theory of micro-markets to categorize the sources of fluctuations in the monthly RMB/USD exchange rate into three major mechanisms: (1) cyclical flows that follow seasonal foreign exchange settlements and sales; (2) those that are jointly determined by the difference in interest rates between China and the United States, and by China's own macroeconomic conditions; and (3) sudden jumps brought about by national policy shocks. By one-medium differencing the series, the ARIMA model is able to exclude non-stationary trends and accurately capture the two types of predictable linear structures; if the residuals are further realized as white noise, then it indicates that the model has adequately explained all the linear information, and the remaining anomalies can be regarded as quantitative proxies for policy shocks.

2.4 Research hypotheses

H1: The residuals of the ARIMA (p,d,q) model fitted to the RMB/USD exchange rate for 2015M4-2025M4 can pass the Ljung-Box white noise test at the 5% significant level.
H2: In the 24-month out-of-sample test for 2023M1-2025M4, the ARIMA model has utility with MAPE $\leq$ 10%.

3 Methodology

3.1 Dataset Processing Methodology

This research primarily utilizes daily closing exchange rates between the RMB and the USD, retrieved from Yahoo Finance. To ensure the continuity and representativeness of the data, the daily data are averaged on a monthly basis after excluding non-trading days. The scope of the data covers the period from April 2015 to April 2025, but considering the exchange rate reform on August 11, 2015, the study excludes data observations prior to that date to ensure contextual consistency.

In terms of data processing, the processed data were converted into time series objects using the ts() function of the R language, setting the frequency to 12 periods per year and taking the natural logarithm of the original series to stabilize the variance. As shown in Figure 1, the series exhibits a certain degree of seasonality and non-stationarity characteristics. In order to maintain the simplicity and interpretability of the benchmark model, this study does not introduce exogenous macro variables, and the modeling analysis is based on this single variable only (see Figure 1).

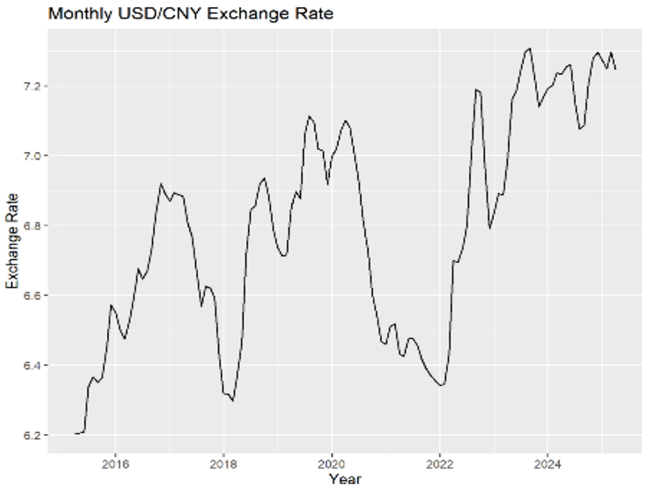

Fig.1. Monthly USD/CNY exchange rate from 2015 to 2025.

3. 2 Dataset Model Modelling

3.2.1 Model Introduction

The classical ARIMA model proposed by Box and Jenkins is used in this study, as it is effective in modeling time series data that exhibit non-stationarity. The ARIMA model removes the effect of trend or seasonality through the differencing operation, before portraying the autocorrelation structure in the series through the AR and MA terms.
When there is significant seasonality in the series, a seasonally extended form of SARIMA can be introduced is:

$$\Phi(B^S)\phi(B)(x_t - \mu) = \Theta(B^S)\theta(B)\omega_t \qquad (1)$$

3.2.2 ARIMA Modeling Based on the Core Dataset

In order to model the time series of the exchange rate of RMB against the US dollar, the study employes the auto.arima() function in R to automate model selection. The function explores various ARIMA model combinations using grid search and evalustes their performance based on criteria like AIC and BIC, so as to select the optimal model. Ultimately, this study identifies the optimal model as ARIMA(2,0,0) with a non-zero mean term. After the model fitting was completed, in order to check whether the residuals conformed to the white noise characteristics, the residuals were diagnosed by using the checkresiduals() function, and with a Ljung-Box p-value of 0.3107-well above the 5% threshold-the result supports the model's adequacy, and therefore the original hypothesis of "residuals are white noise" could not be rejected, indicating that "residuals are white noise" is not a valid hypothesis. The final p-value of the Ljung-Box test is 0.3107, which is much larger than the 5% significance level, and therefore the null hypothesis assuming white noise residuals is not rejected, indicating that the residual terms of the model do not show significant autocorrelation. In addition, the residuals exhibit near-zero autocorrelation values, and the histogram distribution pattern is close to normal (see Figure 2), which further verifies the hypothesis that the residuals obey the white noise distribution. Together, these analytical results support the conclusion that the model can effectively capture the linear structure of the RMB exchange rate data, and its

modeling results are reliable with good fitting quality, providing a solid foundation for subsequent time series studies.

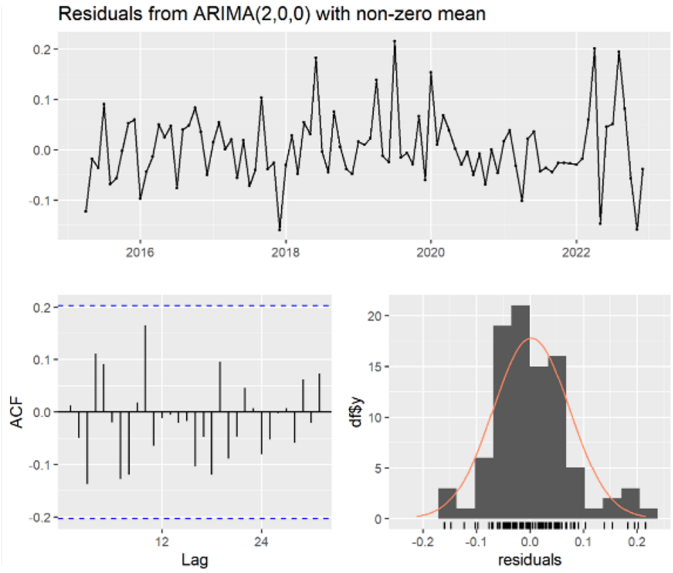

Fig. 2. Residual testing model.

4 Results

In this study, after determining ARIMA(2,0,0) as the optimal model, the RMB/USD exchange rate was analyzed through model fitting on historical data and predictive forecasting on future observations. Figure 3 shows the actual exchange rate from April 2015 to April 2025 and the forecasting results from May 2025 to April 2027. Figure 3 shows the actual exchange rate from May 2025 to April 2027 and the forecasting results. The image shows that the exchange rate experiences a period of upward movement after 2023, but the model predicts a gradual decline starting in mid-2025, with an overall slow downward trend over the next two years. The blue confidence interval (95%) covers most of the range of future trends, indicating that the point forecasts are stable and the interval forecasts are credible.

In terms of the model residuals, the white noise test of the residuals of the ARIMA(2,0,0) model is conducted by using the checkresiduals() function, and the Ljung-Box test yielded a p-value of 0.3107, well above the 0.05 threshold, indicating statistical insignificance, and the original hypothesis cannot be rejected, indicating that the residuals obey the white noise distribution. At the same time, the autocorrelation plot of the residuals reveals no notable lags, with coefficients remaining inside the confidence bounds, and the histogram of the residuals is close to normal distribution. These diagnostic results all indicate demonstrating that the model effectively identifies the underlying linear patterns in the dataset and the fitting results are reliable. Therefore, regarding hypothesis H1: “The residuals of the ARIMA model after fitting the 2015M4-2025M4 exchange rates can pass the Ljung-Box white noise test at the 5% significance level”, it can be confirmed to be valid.

For the assessment of forecasting ability, the model demonstrates predictive accuracy with an RMSE of 0.5565, an MAE of 0.5421, and a MAPE of 7.53% over the out-of-sample forecasting period of January 2023-April 2025, which is well below the 10% threshold for practical application. This result validates the H2 hypothesis: “The ARIMA model has utility

with MAPE ≤ 10% in the 24-month out-of-sample test from 2023M1-2025M4", which also holds.

In summary, the ARIMA(2,0,0) model shows good performance in terms of both model calibration on historical data and generalization to unseen observations: its residuals are characterized by white noise, no obvious structural omissions, the prediction error index meets the preset criteria, and both core hypotheses are empirically supported. The model image shows stable and smooth trend changes, which has the feasibility and application value in short-term RMB exchange rate forecasting.

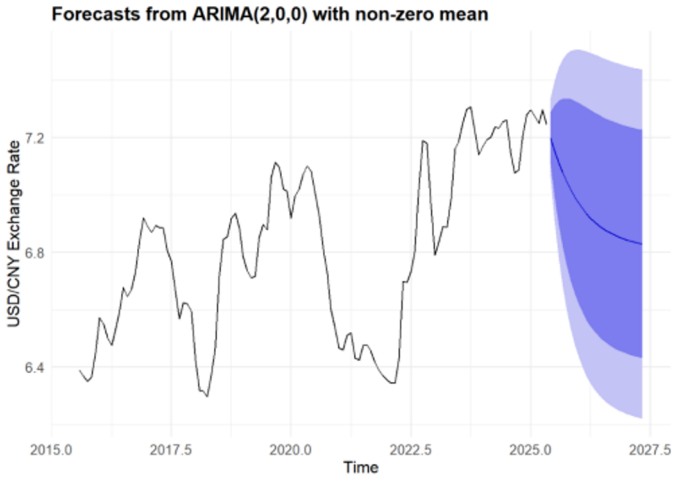

Fig. 3. Forecasts from the ARIMA (2,0,0) model with prediction intervals.

5 Discussion

As mentioned before, this study shows that under China's managed floating exchange rate regime, the ARIMA model-based approach can still provide a useful forecasting tool for exchange rate monitoring and risk management. The Ljung-Box test p-value of the model is 0.3107, and the out-of-sample MAPE is 7.53%, which verifies its statistical validity; meanwhile, the prediction results of the USD-RMB exchange rate show that it will gradually go downward since the middle of 2025, which provides forward-looking decision-making signals for enterprises when facing exchange rate risks. In another study, using an ARIMA model with China's trade balance data, the exchange rate is also predicted to stabilize at 6.7 in 2025, which is highly consistent with the predictive path of this paper [8].

Fluctuations in the RMB exchange rate will directly affect the cost structure and pricing power of Chinese exporters. For processing firms that rely on imported raw materials, RMB appreciation will both compress export profits and reduce material costs, with the net effect depending on whether firms can adjust final commodity prices in a timely manner. The results of this study also support the view that under the trend of gradual RMB appreciation, processing firms should arrange the flexibility of import contracts in advance and make good dynamic adjustments to their export pricing mechanisms, rather than pass on costs through price competition.

For capital-intensive manufacturing firms, the situation is different: a study comparing the ARIMA and LSTM models for forecasting exchange rates, noting that although the deep learning model has lower errors, the ARIMA model is more interpretable in the short run and provides clear confidence intervals, which is helpful for firms to translate their forecasts directly into purchasing cycle or capital expenditure decisions [9]. The ARIMA forecasts in

Figure 3 in this study provide risk intervals for such firms over the next two years, which can help firms make timely purchasing decisions and maintain the stability of their investment rhythms in the face of fluctuations in the prices of imported equipment.

From the perspective of policy tools, the findings support the adoption of transparent and robust statistical benchmark models before using complex machine learning models. One study points out that the introduction of macro forecasting variables into a multivariate ARIMA significantly improves the forecasting accuracy of the USD/EUR exchange rate only if the data quality of the macro forecasting variables is high; in the context of data uncertainty, a simple ARIMA instead in the context of data uncertainty, ARIMA alone is more stable [10]. Therefore, regulators should avoid over-reliance on "black-box modeling" when faced with volatile macroeconomic indicators and unexplained non-structural factors. A better strategy might be to adopt a "two-stage modeling process": the first stage uses ARIMA to extract the linear structure, and the second stage captures the residuals using a nonlinear method, while taking into account the model's interpretability and forecasting accuracy.

Of course, there are some limitations in this paper. First, the model used is a univariate ARIMA, which fails to incorporate macro variables such as spreads, capital flows, or policy shocks; second, this paper uses monthly data, which ignores the potentially important information in daily or weekly high-frequency data. Future research could introduce multivariate structures based on the ARIMA framework, such as hybrid models like ARIMA-GARCH or ARIMA-LSTM, and try higher-frequency data to improve the model's responsiveness to sharp fluctuations. Such improvements will help to enhance the early warning capability of the model and provide more refined forecasting support for policy makers and corporate management.

6 Conclusion

This study is based on the monthly exchange rate data of USD-RMB for the period of April 2015 to April 2025, constructed an ARIMA (2,0,0) model and performed in-sample and out-of-sample forecasting to test its feasibility and accuracy in RMB exchange rate forecasting in the short run. The study verifies the statistical soundness and forecasting efficacy of the model through the evaluation metrics of residual diagnostics, Ljung-Box white noise and MAPE.

This paper aims to answer two core questions: (1) Does the simplified ARIMA model have the ability to provide stable short-term forecasts under the current exchange rate regime? (2) Can the residuals be regarded as proxies for policy or exogenous shocks, thus improving the explanatory power of the model? The empirical results show that both hypotheses are valid, indicating that the ARIMA model still has practical application under the condition of limited data structure.

The innovation of the study is that the univariate time series model can effectively predict the future movement of the RMB exchange rate without introducing any macro variables or deep learning structure, and a credible model framework is constructed by combining the residual white noise test. The study not only improves the interpretability of traditional statistical models in exchange rate forecasting, but also provides policy makers and business managers with operational and replicable quantitative tools.

In summary, the ARIMA (2,0,0) model strikes a balance between transparency, stability, and cost control, and is particularly suitable for application scenarios with limited resources or emphasizing the interpretability of the model. Subsequent studies may build upon this groundwork to refine the model architecture and investigate how macroeconomic indicators can be integrated with nonlinear approaches, thereby improving the model's flexibility and predictive precision.

Reference

1. Y.C. Wang, J.J. Tsai, S. Li, Y. Huang, The impacts of RMB internationalization on onshore and offshore RMB markets. Int. Rev. **Finance 2**3, 502–523 (2023)
2. G.E. Box, G.M. Jenkins, G.C. Reinsel, G.M. Ljung, Time Series Analysis: Forecasting and Control (John Wiley & Sons, New York, 2015)
3. R. Zhang, RMB/USD exchange rate forecasting and analysis by SES and ARIMA model. ResearchGate (2023) https://www.researchgate.net/publication/377746414_RMBUSD_Exchange_Rate_Forecasting_and_Analysis_by_SES_and_ARIMA_Model
4. P.V. Thayyib, M.N. Thorakkattle, F. Usmani, A.T. Yahya, N.H. Farhan, Forecasting Indian Goods and Services Tax revenue using TBATS, ETS, Neural Networks, and hybrid time series models. Cogent Econ. **Finance 11**, 2285649 (2023)
5. S. Siami-Namini, N. Tavakoli, A.S. Namin, A comparison of ARIMA and LSTM in forecasting time series. Proc. 17th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA), 1394–1401 (2018)
6. M. Kaushik, A.K. Giri, Forecasting foreign exchange rate: a multivariate comparative analysis between traditional econometric, contemporary machine learning & deep learning techniques. arXiv preprint arXiv:2002.10247 (2020)
7. S. Meng, A. Chen, C. Wang, M. Zheng, F. Wu, X. Chen, H. Ni, P. Li, Enhancing exchange rate forecasting with explainable deep learning models. Proc. 4th Int. Conf. Electron. Inf. Eng. Comput. Sci. (EIECS), 892–896 (2024) https://doi.org/10.1109/EIECS63941.2024.10800545
8. J. Yin, Forecasting Exchange Rates and Trade Balances: An ARIMA Analysis of USD/RMB and China's Trade Dynamics. Adv. Econ. Manag. Polit. Sci. **46**, 16–24 (2023)
9. F. García, F. Guijarro, J. Oliver, R. Tamošiūnienė, Foreign exchange forecasting models: ARIMA and LSTM comparison. Eng. Proc. 39, **81** (2023)
10. Q. Zhu, Forecasting the US Dollar/Euro Exchange Rate Based on ARIMA Model. Adv. Econ. Manag. Polit. Sci. 15, 371–380 (2023)