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Research on the Volatility of RMB Exchange Rate Based on Time Series Analysis

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Abstract. In recent years, with the rapid development of China's national economy, more and more large-scale overseas transactions have become normalized, and the RMB exchange rate, as the foundation of foreign trade, has taken on increasingly important responsibilities. The RMB exchange rate is steadily advancing in market-oriented exploration, allowing the RMB to occupy an increasingly large proportion in international market transactions. Since 2020, the global economic situation has faced complex and severe challenges, and the fluctuation of the RMB exchange rate has become increasingly complex and frequent. Predicting the exchange rate can help us analyze the economic situation and prevent risks. This article selects the time series of China US exchange rates from November 1, 2017 to October 31, 2022 as the research object to construct different models. R language is used as the implementation software, and multiple models are horizontally compared. Finally, it is found that ARIMA-GARCH (1,1) is more suitable for short-term exchange rate prediction and has higher accuracy. Finally, this article also provides some suggestions for preventing exchange rate risks.

Keywords: exchange rate of RMB, time series, prediction accuracy.

1. Introduction

On July 21, 2005, China began to adopt a new floating exchange rate system, which further enhanced the volatility of the RMB exchange rate and made the conditional heteroscedasticity of fluctuations more severe. Therefore, it is particularly important to model the exchange rate series and extract the variance equation [1]. On August 11, 2015, the People's Bank of China decided to adjust the pricing mechanism for the central parity rate of the Chinese yuan against the US dollar. This adjustment made the Chinese yuan exchange rate more closely linked to the market and better reflected the supply-demand relationship. In summary, the exchange rate changes after the new currency reform have played a significant role in the economy, finance, trade, and other aspects [2]. In 2020, the world economy was greatly impacted, with all economies experiencing some effects, mainly reflected in negative reactions such as a sharp decline in economic growth, an increase in unemployment, and a decrease in trade and cross-border investment. Among them, international trade is also facing severe challenges. International trade is an indispensable part for all economies. Through international trade, scientific and technological levels can be improved, enterprise competitiveness can be enhanced, and national economic levels can be improved. In the research process of international trade, foreign exchange is a variable that cannot be ignored. The change in exchange rate has a guiding effect on the adjustment of national policies, and it is also a lagging indicator of economic conditions. Through the analysis of exchange rate data, it can help us prevent and avoid exchange rate risks [3].

Exchange rate prediction has always been a concern in the field of economic forecasting, and people are constantly advancing in the exploration process of exchange rate prediction. Currently, most exchange rate predictions are made through parameter models. Su Jianping (2012) used macro data from 1990 to 2010 as the research object and analyzed the relationship between the RMB exchange rate and foreign trade development from an econometric perspective using a VAR model. The results showed that through the Granger causality test, there was a bidirectional relationship between the RMB exchange rate and China's foreign trade development. Hu Yulin (2016) established the Copula

GARCH-t model to empirically study volatility, using the yield series of the Chinese yuan against the US dollar, euro, Japanese yen, and Hong Kong dollar for modeling. It was found that the Chinese yuan was most affected by the US dollar, and based on this, policy recommendations for mechanism reform were proposed. Sun Shaoyan and Sun Wenxuan (2019) studied the fluctuation pattern of the RMB exchange rate after joining the SDR, using the midpoint of the US dollar to RMB exchange rate from October 10, 2016, to March 16, 2018, as the research object. They found that selecting a certain lag order ARMA-GARCH model can well characterize the fluctuation trend of the exchange rate. Li Mingxuan (2020) selected the RMB exchange rate over five years as the research object, established ARMA and GARCH models to analyze the data, and concluded that the RMB exchange rate has clustering and leverage. Xiao Wanqiu (2021) selected 30 consecutive US China exchange rate data as sample data, established 15 sub neural networks for prediction, and integrated their results to obtain an integrated network prediction. An optimized BP network with additional momentum was established to compare all results, and it was found that the integrated neural network had higher prediction accuracy [4]. This model has strong logic and significance, but the selected data is relatively small, which limits its accuracy. Xiao Long (2020) constructed an ARIMA model by selecting 24 months of US China exchange rate data to study the short-term fluctuations of the RMB exchange rate and predict the exchange rate trend for the next three months and put forward relevant suggestions.

Existing articles are mostly based on a single model to study the RMB exchange rate. This article draws on and compares the prediction model methods and results of current scholars. This article establishes ARIMA models to fit mean equations to eliminate autocorrelation, establishes GARCH family models to fit volatility equations to eliminate conditional heteroscedasticity, characterizes the volatility characteristics of the RMB exchange rate, and ultimately proposes preventive policies.

2. Theoretical basis

2.1. ARIMA Model

The Autoregressive Integrated Moving Average model was proposed in the 1970s and is mainly used in modeling time series data with stationary properties (which can be transformed into stationary properties). Due to the periodicity of time series, ARIMA transforms non-stationary time series into stationary ones through differential steps, making it more widely used in time series data analysis and also known as classical time series models. The ARIMA model combines the characteristics of autoregression (AR), differencing (I), and moving average (MA).

The autoregressive part uses observations from past time points to predict the current value. Specifically, the current value in the AR (p) model is associated with a linear combination of p past time points. This method is used to capture the autocorrelation within a time series, that is, the relationship between data points and their historical values. The differential part involves performing differential operations on the original time series with the aim of making the sequence stationary. The meaning of a stationary sequence is that its statistical properties (such as mean and variance) are constant over time, without obvious trends or periodic changes. The difference order d determines how many differences need to be made to the original data in order to achieve stationarity. The moving average section considers the linear combination of random error terms (residuals) and their past time points. It helps capture irregular fluctuations in time series and fluctuations that are not explained by other parts of the model.

The general form of the ARIMA model is ARIMA (p, d, q), where p is the order of the autoregressive component and represents the number of autoregressive terms included in the model. D is the number of differential operations used to make the time series stationary. Q is the order of the moving average component, representing the number of moving average terms included in the model.

The ARIMA model is suitable for time series data without obvious seasonality and assumes the stationarity of the data (achieved through differential operations). It can be used to predict future data points, as well as to analyze the trends and periodicity of time series data. It is one of the powerful tools for processing time series data, making predictions and analyses.

2.2. GARCH Model

The GARCH model is a method used for modeling and predicting time series volatility. It is particularly suitable for financial time series data with heteroskedasticity, which refers to situations where volatility has significant changes over time. The main idea of the GARCH model is that volatility is not constant, but rather varies over time and previous periods of volatility. Specifically, the GARCH model combines two parts: the ARCH part (Autoregressive Conditional Heteroskedasticity, which represents the correlation between the volatility at the current time point and the squared residual (volatility) over a period of time in the past. The ARCH effect suggests that large residuals may lead to significant fluctuations in the future, and vice versa. GARCH section (Generalized Autoregressive Conditional Heteroskedasticity): introduces the square of past volatility as an additional factor to capture the autoregressive properties of volatility itself. The GARCH model can better describe long-term volatility changes.

The general form of the GARCH model is usually referred to as GARCH (p, q), where p is the order of the ARCH part and represents the number of squared terms of past residuals contained in the model. Q is the order of the GARCH part, representing the number of squared terms of past volatility included in the model.

The advantage of GARCH model lies in its ability to accurately model volatility in time series data, especially in financial markets, which is crucial for risk management and derivative pricing. Through the GARCH model, future volatility can be predicted, thereby helping investors and decision-makers make more accurate decisions.

3. Empirical Analysis

3.1. Data Source and Processing

This article first selected the daily closing prices of the RMB/USD exchange rate from November 1, 2017, to October 31, 2022, from the Wind database as the dataset, excluding missing data on holidays or individual dates, for a total of 1214 exchange rate closing price data.

3.2. Data Feature

3.2.1. Stationarity Test

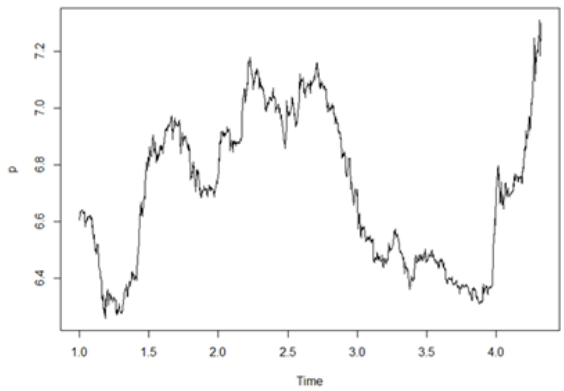

Fig. 1 Time series chart of RMB exchange rate

This article uses R language to test the daily frequency series of the closing price of the RMB/USD exchange rate. p-value=0.990, greater than 0.1, indicates that the original dataset is unstable. Therefore, first-order logarithmic difference processing was performed on the original data to obtain the logarithmic return series. The processing formula is as follows.

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

After first-order difference processing, the data was subjected to stationarity testing with p-value=0.01. The stationarity test was passed, indicating that the data in this group is stable.

3.2.2. Pure Randomness Test

This article first uses R language to perform a pure randomness test on the first-order difference sequence. The test results show that p-value=0.03476 when df=6 and p-value=0.1419 when df=12 is greater than 0.05, indicating that the first-order difference sequence did not pass the pure randomness test. Therefore, we choose to perform second-order difference processing on the original sequence. The second-order difference was subjected to stationarity and pure randomness tests again, and the p-value results were all less than 0.01, passing the pure randomness test. The specific inspection results are shown in the table below.

Table 1. Results of pure randomness test

order		1	2
p-value	DF=6	0.03476	2.2e-16
	DF=12	0.1419	2.2e-16

3.3. Autocorrelation

This article produces corresponding ACF and PACF diagrams for second-order differential sequences, as shown below:

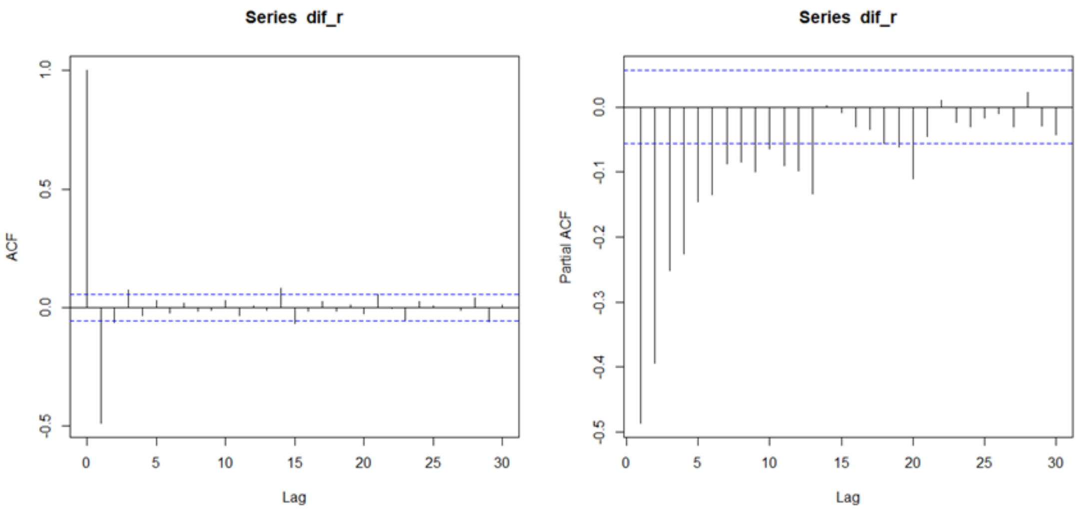

Fig. 2 Autocorrelation and Partial Autocorrelation after Second Order Difference

According to the above figure, it can be determined that the autocorrelation graph has a first-order truncation and is biased towards the tail of the autocorrelation graph. Therefore, it is determined that the ARIMA (0,2,1) model has the best fitting effect.

3.4. Model Checking

By examining the white noise results of the residual sequence, it can be seen that the P-values of the white noise test statistic for each order delay are significantly greater than 0.05. It can be considered that the residual sequence of this fitting model belongs to the white noise sequence, indicating that the fitting model is significantly valid.

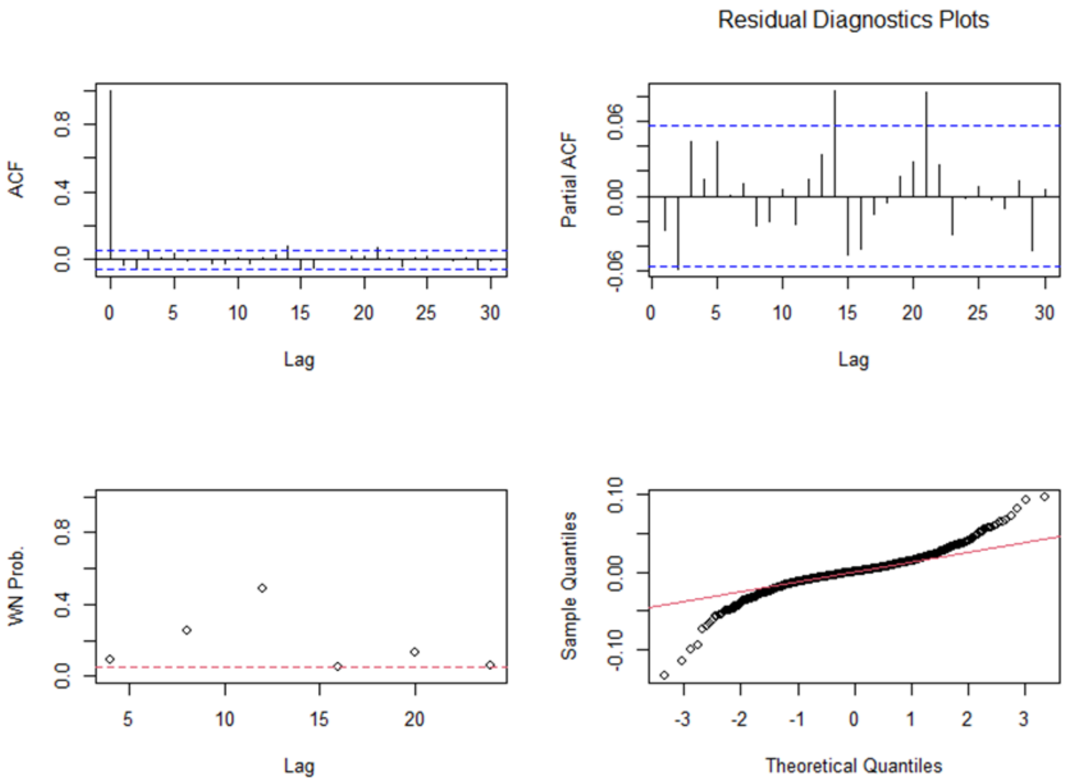

Fig. 3 Significance Test of the Fitting Model for the Closing Price Sequence of the Renminbi Exchange Rate

We obtained the conclusion that the parameters are significantly non-zero using both approximate testing and exact testing methods (constructing parameter significance test t-statistic and calling PT function). The effect diagram of using this model for sequence fitting and prediction is as follows:

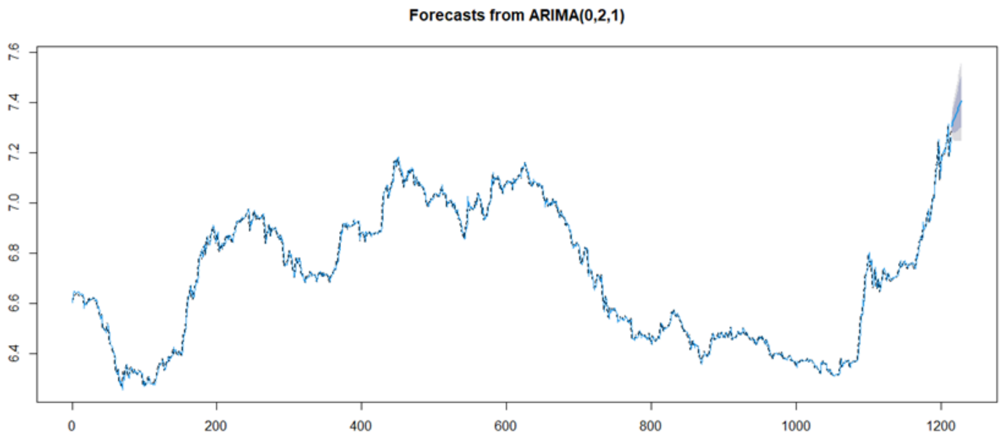

Fig. 4 Fitting and Prediction Results of the Closing Price Sequence of the Renminbi Exchange Rate

4. Further Research

Based on the above description and analysis of autocorrelation, we further introduce the ARIMA-GARCH model and compare the AIC and BIC values of ARCH, GARCH, and EGARCH models. We can select the model with better fitting effect. The specific results are shown in Table 2:

Table 2. Comparison Results of Models

Model	AIC	BIC
ARCH(4)	-10.160	-10.139
GARCH(1,1)	-10.221	-10.204
EGARCH(1,1)	-5.2520	-5.23352

In the case of significant coefficients, considering both AIC and BIC criteria, it was found that the GARCH (1,1) model had the best estimation performance.

5. Conclusions and Recommendations

This article selects the US China exchange rate set from November 1, 2017, to October 31, 2022, as the research object, and establishes ARIMA (0,2,1) models for prediction. Through ARCH testing of the data, it is found that the residuals have clustering. Therefore, we introduce GARCH (1,1) model and EGARCH (1,1) model. Through model comparison, we finally find that GARCH (1,1) has the best effect. After multiple rounds of QE by the Federal Reserve in 2018, with the recent unexpected interest rate hikes, domestic and foreign monetary policies have deviated, and the pressure on the RMB exchange rate has repeatedly exceeded seven.

The current China US relationship is complex, and the external economic situation is not optimistic. As the most important regulatory lever in international trade, the exchange rate will have a significant impact on a country's import and export trade and economic structure. Keeping the RMB exchange rate within a reasonable range not only promotes the healthy operation of China's social economy, but also has significant implications for the sustainable development of other countries around the world [5]. Keeping the RMB exchange rate within a reasonable range not only promotes the healthy operation of China's social economy, but also has significant implications for the sustainable development of other countries around the world. Based on this, the following suggestions are proposed to maintain the stability of the RMB exchange rate:

Firstly, both sides should have a correct view of the friction in Sino US trade, strengthen effective communication between the two sides, reach consensus, and resolve disputes through peaceful means; In the field of Sino US trade, various industries should also strengthen cooperation, actively solve problems in trade, eliminate differences, and clearly recognize the serious harm of trade frictions to both sides. Second, make full use of the opportunity of the "the Belt and Road" to accelerate the pace of RMB internationalization, deepen international monetary cooperation, constantly improve the position of RMB in the world, further highlight its settlement function in the process of foreign trade, promote it to become an international reserve currency, and effectively prevent exchange rate risks that may be caused by trade frictions. Thirdly, we will continue to adhere to and improve the market-oriented exchange rate formation mechanism, maintain the flexibility of the RMB exchange rate, and leverage the role of exchange rate adjustment in macroeconomic and international balance of payments automatic stabilizers to maintain the basic stability of the RMB at a reasonable and balanced level.

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