

Financial Data Analysis Group Project

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Abstract

The change in the exchange rate reflects the economic situation of a country. The increase or decrease in national income, the development of agriculture, the domestic interest rate, and even the domestic employment are impacted deeply by the change of it. The accuracy of exchange rate forecast has great influence on foreign exchange holders, enterprises' import and export trade, foreign exchange trading of individuals and enterprises, foreign exchange holders and so on. With the continuous development of China's economy, in recent years, China's position in the international community has also been strengthened. At present, the CNY and the dollar as the world's most influential two currencies, the exchange rate fluctuations on the global financial and economic development have played a decisive role in the global market.

This paper establishes the GARCH model and ARIMA model of CNY exchange rate fluctuation, and deals with the exchange rate that China has established since 2005. We hope to make a comparison between two of them. Through the establishment and prediction of the measurement model, we find that *GARCH*(1, 1) model is the appropriate one to forecast the exchange rate. And we hope that this conclusion can provide some reference for the central bank's control measures and the exchange rate reform policy.

Key Words: ARMIA, GARCH, CNY exchange rate, Comparison, Prediction

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1 Introduction

An exchange rate between two currencies is the rate at which one currency will be exchanged for another. It is also regarded as the value of one country's currency in relation to another currency. Exchange rates are determined in the foreign exchange market, which is open to a wide range of different types of buyers and sellers, and where currency trading is continuous. US Dollar(USD,\$) is considered as the most influential currency in the world and Chinese Yuan(CNY,) shows increasing power in the international environment. Thus, discussing the relationship between the two currencies is quite meaningful.

Each country determines the exchange rate regime that will apply to its currency. For example, the currency may be free-floating, pegged (fixed), or a hybrid. The Central Committee and the State Council promulgated the reform of the CNY exchange rate formation mechanism on July 21, 2005. The CNY exchange rate was no longer pegged to a single dollar, and fluctuated according to the market supply and demand. After August 11, 2015, the correlation between the CNY and the dollar index has declined. In 2016, the annual depreciation of CNY is about 6.67%, against a basket of currency depreciation rate is 5.13%. But the degree of marketization of the CNY in 2016 significantly increased, and gradually drops out of the “dollar anchor”. CNY exchange rate changes as China's international financial relations and even the normal development of economic relations. It is an important link and plays an increasingly important role. Therefore, it has a vital significance to correct analysis and forecast the exchange rate and its volatility for the economic subject of financial policy and investment and financing decision-making undoubtedly. Also, to predict USD / CNY exchange rate better, it is very important to choose a satisfactory model.

Many domestic scholars have studied this based on time series measurement method. Which model of ARIMA model, ARCH model or GARCH model is more appropriate for the exchange rate fluctuations is controversial. Zhang(2005) suggested that the exchange rate change was fit into $ARIMA(2, 4, 5)$ model. Hui(2005) argued that there was a GARCH effect in the time series of USD / CNY, and the $GARCH(1, 1)$ model was suitable for USD / CNY modeling. Xu and Li(2007) used the ARMA model to forecast the exchange rate of the euro and yen of a basket of currencies and calculated the future exchange rate of the yuan against the US dollar according to the CNY benchmark exchange rate formula. Liu(2008) selected data of the changes in the daily parity of CNY against the US dollar from Jul.25th, 2005 to Nov.1st, 2007 and stated that the $GARCH(1, 1)$ model and the $ARMA(1, 1)$ model are all suitable. Zhai(2009) showed that the CNY exchange rate volatility had certain leverage effect and the CNY exchange rate did not have the characteristics of floating exchange rate regime through the TGARCH model empirical study. Luo(2009) analysed the exchange rate volatility model established from the data after the reform of China's exchange rate system. The study shows that there existed ARCH effect in China's foreign exchange market and $GARCH(1, 1)$ was suitable.

It is not difficult to point out that the data of previous studies are mostly old, while the appropriation of the model will change with the background of the times and the

change of the data. In recent years, the international situation has been changed largely, so we are going to do an empirically research on the ARCH model, ARIMA model and GARCH model and to compare which forecasting model of CNY is more suitable for China and the development situation.

2 Data Source and Data Description

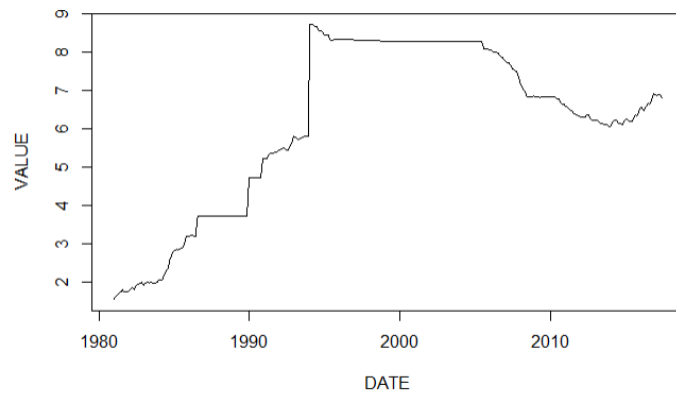
2.1 Data Source

We collected monthly USD / CNY exchange rate from 1981-01-01 to 2017-06-01, and daily exchange rate data from 2005-07-21 til 2017-06-09 from Federal Reserve System. According to the system, the data are already wiped out the seasonal effect.

2.2 Data Description

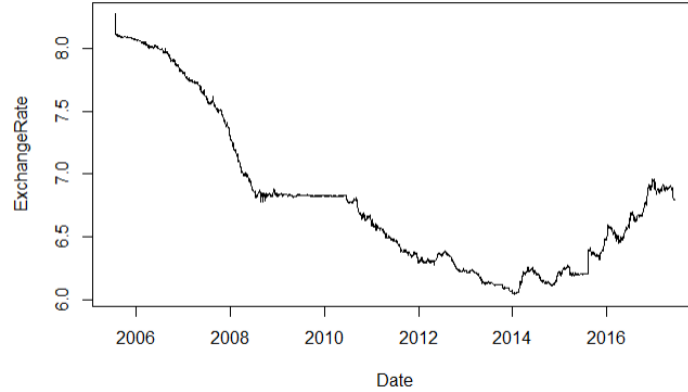
We first use monthly USD / CNY exchange rate data to plot a trend figure shown as figure 1. According with the news, China used to set fixed exchange rate mechanism before 2015-07-21, the volatility of exchange rate was small. After that date, China started exchange rate regime reforming: announced a move away from the US dollar peg and used a floating exchange rate. Thus in this paper we will mainly focus on analysing exchange rate after the reform.

Figure 1: CNY/ USD Exchange Rate using monthly data



We collected the daily USD / CNY exchange rate as our data set. The data we found are already wipe out the seasonal effect so we use them directly in examining the model and further doing forecast. We divided the data into two parts one until July 21st,2016 for examine the model and the data after that date until June 9th,2017 for checking the evaluation of the models. The trend figure is shown in figure 2.

Figure 2: USD / CNY Exchange Rate using daily data



3 Model Specification

There are usually two ways in analysing the exchange rate in time series: ARIMA model and GARCH model since they are the more general form of an ARMA model and an ARCH model.

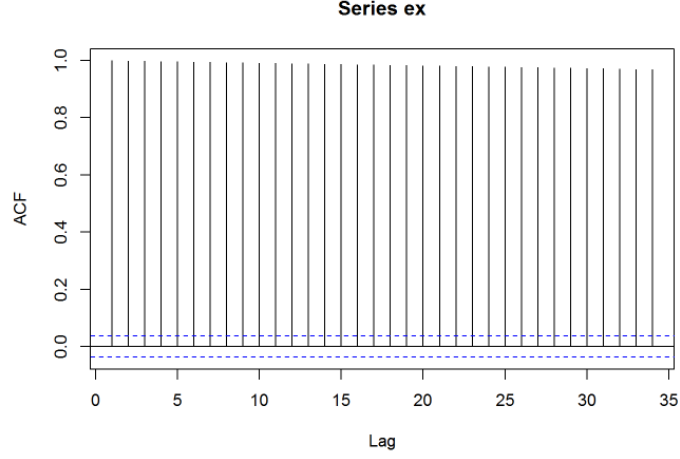
3.1 Autoregressive Integrated Moving Average Model

An Autoregressive Integrated Moving Average (ARIMA) model is a generalization of an Autoregressive Moving Average (ARMA) model with unit roots. Basically an ARMA model combines the ideas of Autocorrelation (AR) model and Moving Average (MA) model but it models with less number of parameters, achieving parsimony in the model. The general $ARMA(p, q)$ form is like $r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} + a_t - \sum_{i=1}^q \theta_i a_{t-i}$ where a_t is a white noise series. An AR model forms a multiple linear regression model with lagged values serving as the explanatory variables. A MA model is an infinite-order AR model with some parameter constraints. And the “I” of Integrated indicates data values have been replaced with the difference between their values and the previous values.

To begin with, we want to check if the daily exchange rate series exists a unit root in the series. As mentioned before, we first use the first 2766 data (from 2005-07-21 to 2016-07-21) to check the ACF of series. From figure 3, we can say that ACF shows a strong autocorrelation which almost does not decay indicates the existence of unit root. We also run an ADF-test double-check the unit-root result. The ADF-test statistic is -3.1048 with p-value 0.0274, which is larger than 0.01, so the unit-root hypothesis cannot be rejected under 1% significant level.

```
origin=da$ExchangeRate
ex=origin[1:2766] # 2005-07-21 To 2016-07-21
acf(ex)
pacf(ex)
```

Figure 3: ACF results of exchange rate series



```
# ADF Test
adfTest(ex, lags=m1$order, type=c("c"))
##
## Title:
## Augmented Dickey-Fuller Test
##
## Test Results:
## PARAMETER:
## Lag Order: 12
## STATISTIC:
## Dickey-Fuller: -3.1048
## P VALUE:
## 0.0274
```

However, when we want to further estimate a ARIMA model, the autocorrelation between the 8th difference exchange rate are still significant at lag 13th. Unlike Zhang(2005) who successfully estimated an $ARIMA(2, 4, 5)$ model using monthly data from Jan. 1989 to Dec.2003, we try to estimate an $ARIMA(6, 4, 12)$ model but end with unideal results. Thus, we focus on ARCH and GARCH model in the following research.

3.2 General Autoregressive Conditional Heteroscedastic Model

A General Autoregressive Conditional Heteroscedastic(GARCH) model is an extension of Autoregressive Conditional Heteroscedastic(ARCH) model. It shows the parsimonious of the parameters to adequately describe the volatility process of a series. The most commonly used GARCH model is $GARCH(1, 1)$, and its form is like $a_t = \sigma_t \epsilon_t$, $\sigma^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ where $0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$.

We first estimate an ARCH(1) model, results are like

$$\begin{aligned} r_t &= 1.9966 + a_t \\ \sigma_t^2 &= 6.055 * 10^{-07} + 1.000a_{t-1}^2 \end{aligned}$$

Figure 4: ARCH(1)

Standardised Residuals Tests:					
			Statistic	p-Value	
Jarque-Bera Test	R	Chi^2	407.1392	0	
Shapiro-Wilk Test	R	w	0.6780088	0	
Ljung-Box Test	R	Q(10)	24517.65	0	
Ljung-Box Test	R	Q(15)	35731.26	0	
Ljung-Box Test	R	Q(20)	46652.09	0	
Ljung-Box Test	R^2	Q(10)	38.49667	3.109177e-05	
Ljung-Box Test	R^2	Q(15)	53.9964	2.630455e-06	
Ljung-Box Test	R^2	Q(20)	58.15351	1.369756e-05	
LM Arch Test	R	TR^2	43.46774	1.881081e-05	
Information Criterion Statistics:					
	AIC	BIC	SIC	HQIC	
	-3.765512	-3.759086	-3.765515	-3.763191	

And an ARCH(3) model,

$$\begin{aligned} r_t &= 1.9966 + a_t \\ \sigma_t^2 &= 5.675 * 10^{-7} + 0.9953a_{t-1}^2 + 1.000 * 10^{-8}a_{t-2}^2 + 0.01381a_{t-3}^2 \end{aligned}$$

Figure 5: ARCH(3)

Standardised Residuals Tests:					
			Statistic	p-Value	
Jarque-Bera Test	R	Chi^2	401.1047	0	
Shapiro-Wilk Test	R	w	0.6802692	0	
Ljung-Box Test	R	Q(10)	24436.1	0	
Ljung-Box Test	R	Q(15)	35600.29	0	
Ljung-Box Test	R	Q(20)	46469.15	0	
Ljung-Box Test	R^2	Q(10)	39.27942	2.268141e-05	
Ljung-Box Test	R^2	Q(15)	53.69209	2.957023e-06	
Ljung-Box Test	R^2	Q(20)	57.03984	2.024238e-05	
LM Arch Test	R	TR^2	39.57381	8.4608e-05	
Information Criterion Statistics:					
	AIC	BIC	SIC	HQIC	
	-3.762501	-3.751790	-3.762508	-3.758633	

Also an GARCH(1,1) model,

$$\begin{aligned} r_t &= 2.0576 + a_t \\ \sigma_t^2 &= 6.144 * 10^{-9} + 0.1619a_{t-1}^2 + 0.8440\sigma_{t-1}^2 \end{aligned}$$

Figure 6: GARCH(1,1)

Standardised Residuals Tests:					
			Statistic	p-Value	
Jarque-Bera Test	R	Chi ²	8835.812	0	
Shapiro-Wilk Test	R	W	0.7412733	0	
Ljung-Box Test	R	Q(10)	20267.05	0	
Ljung-Box Test	R	Q(15)	29406.02	0	
Ljung-Box Test	R	Q(20)	38281.3	0	
Ljung-Box Test	R ²	Q(10)	6.427786	0.778134	
Ljung-Box Test	R ²	Q(15)	7.322057	0.948089	
Ljung-Box Test	R ²	Q(20)	7.703267	0.993656	
LM Arch Test	R	TR ²	6.251706	0.9028656	
Information Criterion Statistics:					
	AIC	BIC	SIC	HQIC	
	-4.166226	-4.157658	-4.166231	-4.163131	

4 Estimation and Result Analysis

As the results above, we can find the GARCH(1,1) model have the highest likelihood with the lowest AIC and BIC, while the considering the alpha, ARCH1 model is also appropriate. Further, Ljung box test is needed to decide which model is better. If p value is less than 0.05, we can reject the null hypothesis, seeing the model is appropriate. As we can see from the results, GARCH(1,1) model is suitable for the volatility and mean equation.

Here is the prediction we made

Figure 7: point forecast

	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2767		2.037749	2.036294	2.039205	2.035523	2.039976
2768		2.037716	2.035652	2.039781	2.034559	2.040874
2769		2.037690	2.035143	2.040237	2.033795	2.041585
2770		2.037669	2.034707	2.040631	2.033139	2.042199
2771		2.037652	2.034318	2.040986	2.032554	2.042750
2772		2.037638	2.033965	2.041312	2.032020	2.043256
2773		2.037628	2.033639	2.041616	2.031528	2.043728
2774		2.037619	2.033335	2.041903	2.031067	2.044170
2775		2.037612	2.033050	2.042174	2.030634	2.044590
2776		2.037606	2.032780	2.042433	2.030225	2.044988

5 Conclusions

Having seen from the result, the test results showed the detection model possesses preferable practicability. The exchange rate volatility equation is significant in GARCH model. This method have little error, the estimate result is pretty ideal. According to the analysis, we can see the exchange rate fluctuated remarkably, which is not normal distribution. According to the results, it seems feasible to use this model to predict the exchange rate revealing the upward tendency for the CNY. Along with the SDR, CNY gradually move

in the line with the trend of the international financial market, while the non-stationary means it still needs to take measures to prevent the risk of the sharp appreciation and depreciation.

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6 Appendix

6.1 Additional R code

```
library(readxl)
library(timeDate)
library(timeSeries)
library(TSA)
library(fUnitRoots)
library(forecast)

data <- read_excel("D:/Junior/GitHub/FDA_project_LYF/Data/MonthlyData.xlsx")

head(data)
dim(data)

plot(data, type="l")

da <- read_excel("D:/Junior/GitHub/FDA_project_LYF/Data/DailyData.xlsx")

head(da)
dim(da)

plot(da, type="l")

# Take difference
dex2=diff(dex)
dex3=diff(dex2)
dex4=diff(dex3)
dex5=diff(dex4)
dex6=diff(dex5)
dex7=diff(dex6)
dex8=diff(dex7)
acf(dex8)
pacf(dex8)

#ARIMA
m2=arima(ex, c(6, 4, 12))
m2
Box.test(m2$residuals, lag=30, type = "Ljung")
pv2=1-pchisq(776.93, 12)
pv2

Call:
arima(x = ex, order = c(6, 4, 12))
```

```

Coefficients:
              ar1          ar2          ar3          ar4          ar5          ar6          ma1
ma2          -0.8638   -0.1001   0.0419   -0.0185   0.0187   -0.0084   -1.6103
0.3084
s.e.          NaN          NaN          NaN          NaN          NaN          0.0004          NaN
0.0003
              ma3          ma4          ma5          ma6          ma7          ma8          ma9
ma10          ma11
              0.2579   -0.0777   0.1486   -0.033   0.0986   -0.0976   0.1079   -0.095
-0.1169
s.e.          NaN          NaN   0.0001          NaN   0.0002          NaN          NaN
NaN   0.0004
              ma12
              0.1103
s.e.   0.0003

sigma^2 estimated as 0.0001398:  log likelihood = 8328.14,  aic = -16620

Box-Ljung test

data:  m2$residuals
X-squared = 776.93, df = 30, p-value < 2.2e-16

```