MODELING THE RMB EXCHANGE RATE VOLATILITY

USING ARCH/GARCH MODELS

by

LINGXUE SONG

JAMES WANG, COMMITTEE CHAIR

SHAN ZHAO
JUN MA

A THESIS

Submitted in partial fulfillment of the requirements for
the degree of Master of Arts
in the Department of Mathematics
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2016

ABSTRACT

China has reformed the RMB exchange rate regime since 2005. Before 2005, a purely fixed exchange rate policy was implemented in China. After reforming the exchange rate policy, China allows the RMB exchange rate to float under certain fluctuation range. The fluctuation band has been widened several times during the past ten years. How does the RMB exchange rate fluctuate? What does the RMB exchange rate volatility look like? Does the widening of the fluctuation band affect the RMB to USD exchange rate volatility? This thesis is devoted to explore some answers of these problems.

This thesis uses a combination of theoretical and empirical analysis to study the fluctuation dynamic of RMB exchange rate against the USD by using the ARCH/GARCH models. In our analysis, five dummy variables are added in the GARCH model. The coefficients of the dummy variables can reveal the effects of the fluctuation range changes on the RMB exchange rate volatility.

A few conclusions can be drawn from our analysis. The ARCH family models can well fit the clustering of RMB exchange rate volatility. By using the ARCH/GARCH models our analysis indicates that widening the exchange rate fluctuation band does affect the exchange rate volatility.

LIST OF ABBREVIATIONS AND SYMBOLS

AR	Autoregressive
MA	Moving average
ARCH	Autoregressive conditional heteroskedastic
GARCH	Generalized autoregressive conditional heteroskedastic
WTO	World Trade Organization
PBOC	People’s Bank of China
IMF	International Monetary Fund
SDR	Special Drawing Right
ADF	Augmented Dickey-Fuller
AC	Autocorrelation
PAC	Partial autocorrelation
LM	Lagrange multiplier
AIC	Akaike information criterion
SC	Schwarz criterion

ACKNOWLEDGMENTS

I am pleased to have this opportunity to thank my teachers, family, friends, and faculty members who have helped me with this research thesis. I am most grateful to James Wang, the committee chair of this thesis defense, for sharing his mathematical expertise and wisdom. I am also grateful for all of my committee members, Shan Zhao and Jun Ma, for their encouragement and inspiring advises on my academic improvement. I would like to thank Chi-Yang Chu for his help in instructing me in EViews.

I would also like to thank some of my friends for attending my defense and encouraging me. Also, this thesis would not have been completed without the support of my family in China. They never stopped encouraging and supporting me. Finally, I thank my university, the University of Alabama, where I have spent six years for receiving great useful education in Finance and Math.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

a. Contents Arrangement

This thesis consists of four chapters.

Chapter 1 is an introduction. In this part, an introduction to the backgrounds of the research and China's exchange rate policies is given. Also, we will briefly describe the concepts of time series and autoregressive models, and the ARCH models.

Chapter 2 elaborates some related theoretical basis. Also, it analyzes the China Renminbi to US Dollar exchange rate trend, and concisely explains the economic phenomenon behind the trend.

Chapter 3 analyzes the RMB to USD spot exchange rate from 8/1/2005 to 12/31/2015 using the ARCH family models, and shows that widening the fluctuation band does affect the RMB exchange rate volatility. During the modeling, several dummy variables are added, to make the model fit the characteristics of the exchange rate volatility better.

Chapter 4 draws the conclusion that the ARCH/CARCH models can well fit the RMB to USD exchange rate volatility, and widening the fluctuation band does affect the exchange rate volatility. Finally, some simple suggestions on China's exchange rate reforms are offered.

b. Research Backgrounds

i) The Impossible Trinity

In economics, the Impossible Trinity is the rule that a country cannot have an independent monetary policy, a free capital movement and a fixed exchange rate at the same time.

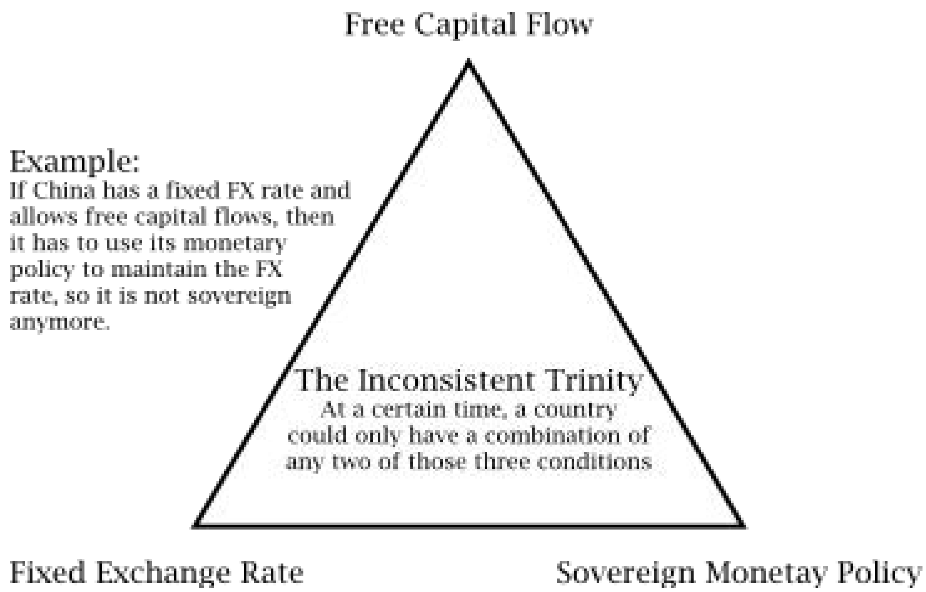

Figure 1. The Impossible Trinity

In international economics, the trilemma requires that a nation or central bank can only achieve two of the three conditions. From empirical studies, the historical experience tells us that governments which have tried to simultaneously achieve all three goals have failed. Nowadays, most countries implement the floated exchange rate, to pursue an independent monetary policy and free capital flow.

ii) Reform of China's Exchange Rate Regime

For a long time, China had a purely fixed exchange rate before 2005. In China's fixed exchange rate regime, the Chinese yuan was only pegged to the U.S. dollar at approximately

8.28. However, since joining the World Trade Organization (WTO), China has paced into the world more and more quickly. The Chinese government realized that it is imperative to achieve a free flow of capital. Therefore, a more flexible exchange rate regime is needed, and a floating exchange rate system has become the inevitable choice of China's exchange rate reform. In order to adapt to economic globalization and achieve smooth transition to floating exchange rate system, in May 2005, the People's Bank of China (PBOC), China's central bank, announced the abolition of the original dollar exchange rate system, revalued the yuan, began to implement a managed floating exchange rate system on the basis of market supply and demand, referencing to a basket of currencies conditions including the USD, the Euro, the Japanese Yen, and the Korean Won, and adjusted the range of fluctuation of RMB against USD trading price. This type of regime is actually a fusion of a fixed and floating currency.

iii) Benefits from Exchange Rate Reform

After reforming the exchange rate regime, China's participation in the global economy is more actively and positively. In 2012, U.S. became China's largest export market. In 2013, China became the biggest source of imports, second-largest trading partner, and third-largest export market of the United States. Nowadays China's foreign trade is the largest in the world by volume. So, the RMB exchange rate regime draws many countries and economic entities' attention. During the past ten years, China has been under increasing pressure to let its currency strengthen to even out global trade imbalances, especially the U.S. calls for the appreciation of the RMB.

On November 30, 2015, the International Monetary Fund (IMF) agreed to include China's RMB in the Special Drawing Right (SDR) currency basket. This decision marks another cornerstone in China's global economic emergence. The IMF Survey article *Chinese Renminbi to Be Included in IMF's Special Drawing Right Basket* points out that: "It is also recognition of the progress that the Chinese authorities have made in the past years in reforming China's monetary and financial systems." People believe that this decision will expedite the process that China reforms its currency system more freely floated. So far, China still does not allow the full flexibility of exchange rate, but China allows for pegging the yuan to the U.S. dollar at a daily reference rate set by the PBOC and allows the currency to fluctuate within a fixed band on either side of the reference rate. During the past ten years, China has adjusted and widened the range of fluctuation band several times. The band was 0.3% from 2005 after reforming the exchange rate. In May 2007, the PBOC widened the range from 0.3% to 0.5%. During the financial crisis in 2008, to confront the severe and complex economic situation, the PBOC again pegged the RMB to the USD. In June 2010, China rebooted the reformed exchange rate system. In April 2012, the PBOC increased the fluctuation range from 0.5% to 1%. Then in March 2014, the band was widened from 1% to 2%. Until now, investors are allowed to push the yuan's value 2% in either direction from that rate in daily trading.

From these bright changes of economy status and the improvements of China's participation in global market, we have reasons to believe that the reformed RMB exchange rate promotes the development of China's economy. With the deepening of the exchange rate reform, the exchange rate fluctuation band is widening. And the widening exchange rate fluctuation band keeps influencing the exchange rate volatility, which helps the exchange rate accommodate itself to the global market. Under China's current economic condition, we encourage the Chinese government to continue to implement the managed floating exchange rate system.

c. Backgrounds of ARCH models

i) Time Series & Autoregressive Model

A time series is a sequence of data points made over a continuous time interval and out of successive measurements across the interval. The measurements are usually made using equally spaced times, such as, daily, monthly or yearly.

The analysis of time-series data is of vital importance to economic and financial world. For example, macroeconomists study on the behavior of domestic and international economies to predict the supplies and demands of markets; finance economists analyze the stock market to forecast the ups and downs of stock prices.

In an autoregressive (AR) model, a value is regressed on previous values from the same time series. The equation of the AR model of a time series y_t at order p, AR (p), can be expressed as:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + \varepsilon_t$$

Where y_{t-p} is its lagged variable at time (t-p). The residual term at time t, ε_t, is independent and identically distributed with white noise.

ii) Homoscedasticity vs. Heteroscedasticity

In the AR model, the current value of the time series process is a weighted sum of the past values, plus an error term or innovation or white noise which is independently and identically distributed. Also the weights are fixed. All the stochastic changes at each time are derived from the same distribution. This model is called homoscedasticity. However, in the real world, many financial and economic phenomena appear to be heteroscedasticity, which refers to the circumstance in which the variability of a variable differs from others. Sometimes they appear to have volatile periods followed by calm periods.

In algebraic way, we can express the homoscedasticity as:

$$Var(\varepsilon \mid X) = \sigma^2$$

This means that, regardless of the predictor variable X , the variance of the error term ε is the same. But if the assumption above violates, i.e.

$$Var(\varepsilon \mid X) = \sigma^2 h(X)$$

Then we say the error term is heteroskedastic.

iii) Autoregressive Conditional Heteroskedastic Model

In econometrics, autoregressive conditional heteroskedastic (ARCH) models, which are AR models with conditional heteroscedasticity, are commonly used to characterize and model time series. They can be applied at any point in a series, and the error terms are regarded to have a characteristic size or variance. In particular ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms - often the variance is related to the squares of the previous innovations. ARCH models are commonly employed in modeling financial time series that exhibit time-varying volatility clustering. While conventional time series and econometric models operate under an assumption of constant variance, the ARCH process, advanced by Robert F. Engle (1982), allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. Domowitz and Hakkio (1985) found that the U.S. dollar exchange rate volatility had the ARCH effect using GARCH model and tested that the exchange rate volatility was related to some key macroeconomic variables such as interest rate. Baillie and Bollerslev (1992) considered predictions from a general dynamic time series model with ARMA disturbances and time-dependent conditional heteroscedasticity by a GARCH process. Xiaofeng Dai and Qingxian Xiao (2005) fitted the USD/RMB daily exchange rate volatility of 2003 using ARMA and EGARCH. Zhibin Li and Yuan Liu (2010) analyzed the properties of the RMB exchange rate volatility based on the exchange rate from 2005 to 2007 by using the ARCH models.

In 2003, Engle won the Nobel Prize in Economics “for methods of analyzing economic time series with time-varying volatility (ARCH)”.

CHAPTER 2

THEORETICAL BASIS

a. Volatility Characteristics of Financial Assets Returns

Volatility is a statistical measure of dispersion, which simply is how much a variable varies, of financial assets returns. High volatility means that the value or price can potentially change significantly in a short time. While low volatility means that the value or price fluctuates at a steady pace over a period of time. Usually the volatility appears the non-equilibrium state. Exchange rate volatility is a measure of the fluctuations in an exchange rate. Exchange rate volatility also follows the characteristics below.

The most common characteristics of the volatility are:

i) Fat tail

A fat-tailed distribution is a heavy-tailed statistical distribution which describes the probability. As the diagram below shows, compared to the normal distributions, fat tails have a sharper bell shape.

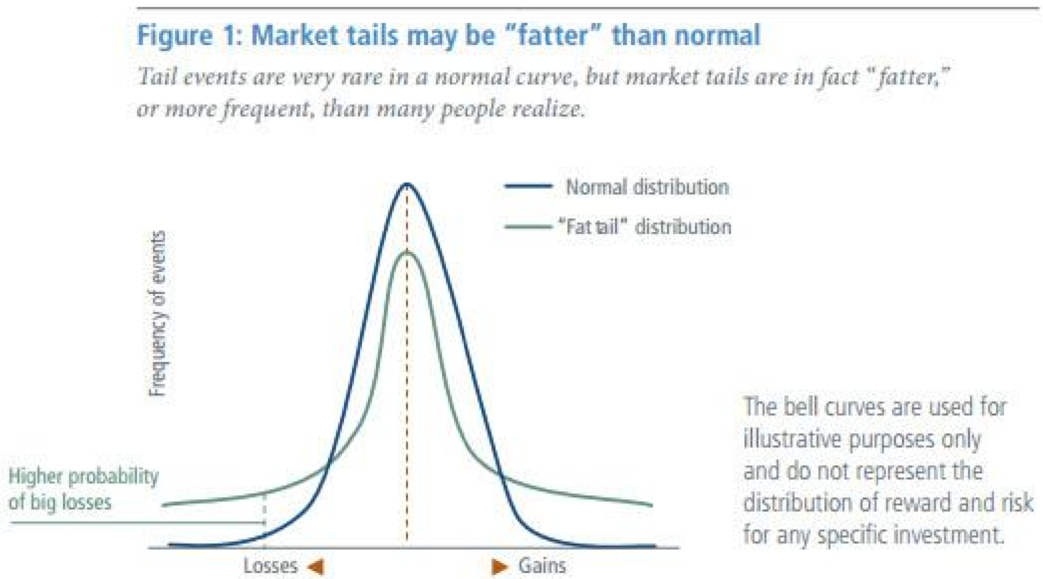

Figure 2. Fat Tail Figure

When we observe the distribution of financial time series such as exchange rate returns, there exists fatter tails than the normal distribution. This observation is also referred to as excess kurtosis. Benoît Mandelbrot (1960) put forth that the rate of return of financial market followed the Levy distribution, not the normal distribution. Nassim Taleb, and Fama (1965) proved and advanced this feature.

ii) Volatility clustering

Volatility clustering is the tendency of big changes in financial assets returns or prices to cluster together. Benoit Mandelbrot (1963) put forth that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes". This explains the volatility clustering which has been observed in finance.

For example, the diagram below shows a sample of NASDAQ daily returns. The returns appear to fluctuate clusteringly. The large changes in the return tent to cluster together, and small changes in the return tend to cluster together. This characteristic exhibits the volatility clustering.

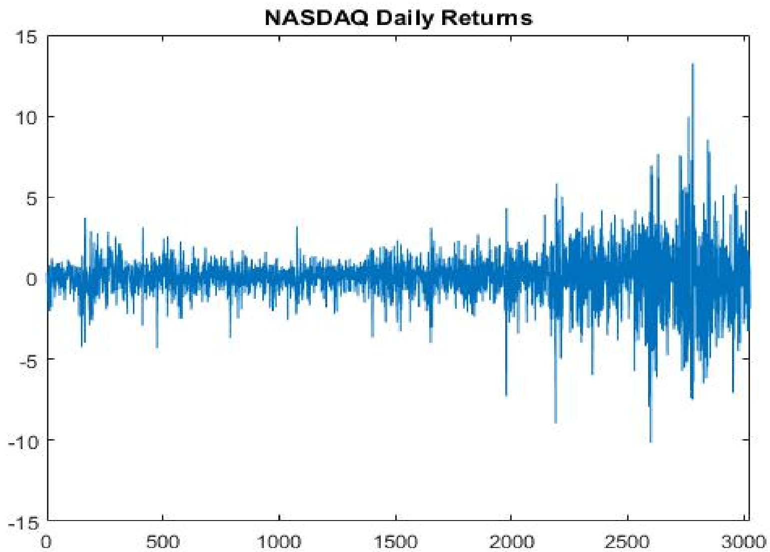

Figure 3. Volatility Clustering Figure

iii) Long memory

Long memory in volatility occurs when the effects of volatility shocks decay slowly which is often detected by the autocorrelation of measures of volatility, such as absolute or squared returns. This feature especially appears in high-frequency data like exchange rates. Granger and Joyeux (1981) and Hoskin (1981) fractionally integrated series was shown to exhibit long memory property.

b. RMB to USD Exchange Rate Trend Analysis

Figure 4. RMB to USD Exchange Rate Trend

The chart above shows the correlation between the USD and the CNY.

From the August 2005 to June 2008, there was a rapid appreciation of the RMB. The reasons of this phenomenon were complex. During this period, China started to implement the reformed exchange rate regime, and the international market demand and the pressure from other countries, as well as the USD's appreciation, drove the RMB to be revalued constantly. But from June 2008 to June 2010, due to the financial crises, China again only pegged to the U.S. dollar, to try to deal with the severe economic climate. So as shown in the chart, the RMB exchange rate during this period remained fixed. From June 2010, the PBOC restarted the managed floated exchange rate, and the RMB exchange rate experienced a slow appreciation, till the first quarter of 2014. From the beginning of 2014 until now, the yuan has depreciated a little, because of the slower speed of domestic economy growth and the sharp depreciation of the USD.

From these periods of the RMB exchange rate dynamic, we can find that the volatility of the USD plays a vital role on China currency's fluctuation. The USD's appreciation or depreciation influences the trend of the RMB deeply. Therefore, in order to maintain the stability of the RMB exchange rate, it is an effective method to increase the flexibility of the RMB to USD and widen the fluctuation band of the RMB exchange rate.

CHAPTER 3

MODELING CNY/USD EXCHANGE RATE VOLATILITY

a. ARCH Models

i) The ARCH model

The ARCH model expects that the variance of residual at time t is related to the residuals of previous periods. An ARCH process of order p, where p is the number of autoregressive lags imposed on the equation, can be written as follows:

$$y_t = b_1 y_{t-1} + b_2 y_{t-2} + \cdots + b_p y_{t-p} + \varepsilon_t$$
$$\varepsilon_t \mid I_{t-1} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2$$

Where y_t is a time series variable at time t. y_{t-p} is its lagged variable at time (t-p). The residual term at time t, ε_t, is independent and identically distributed with white noise. σ_t^2 is the conditional variance. To ensure the conditional variance is non-negative, we assume $\alpha_i \geq 0, i = 1, \cdots, p$

From the functions we can notice that the conditional variance σ_t^2 is determined by $\varepsilon_{t-1}^2, \ldots, \varepsilon_{t-p}^2$. When ε_{t-1} is big, the variance of the residual term at time t is big; and when ε_{t-1} is small, the variance of the residual term at time t is also small. So ARCH (p) model can reflect the volatility characteristics of financial market variables, especially the volatility clustering, that is, large changes tend to be followed by large changes, and small changes tend to be followed by small changes.

ii) The GARCH model

Bollerslev generalized the ARCH model in 1986. The generalized ARCH model, or GARCH, models current conditional variance with geometrically declining weights on lagged squared residuals. The lags used by the model are explicitly stated by GARCH (p, q), where p is the number of autoregressive lags, and q is the number of moving average lags. The GARCH (p, q) model can be expressed as:

$$y_t = b_1 y_{t-1} + b_2 y_{t-2} + \cdots + b_p y_{t-p} + \varepsilon_t$$
$$\varepsilon_t \mid I_{t-1} \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{q} \beta_k \sigma_{t-k}^2$$

Where $p \geq 1, q \geq 1; \alpha_i \geq 0, \beta_i \geq 0$.

The GARCH model works better on forecasting the volatility, since it has long-term memory and also gives recent values more weight. Generally speaking, GARCH (1, 1) process is enough to capture the volatility clustering. Thus, researchers seldom use higher levels of GARCH model.

b. The Data

This thesis collects the daily spot RMB to USD exchange rate from 8/1/2005 to 12/31/2015, giving a total of 2719 observations. All the data comes from Federal Reserve Bank of St. Louis website and State Administration of Foreign Exchange of China website. In addition, EViews is used in this thesis as the statistical software.

To observe the fluctuate dynamic of the daily exchange rate, we calculate the daily percent changes using the data with the formula: $\%change = (y_t - y_{t-1}) / y_{t-1}$.

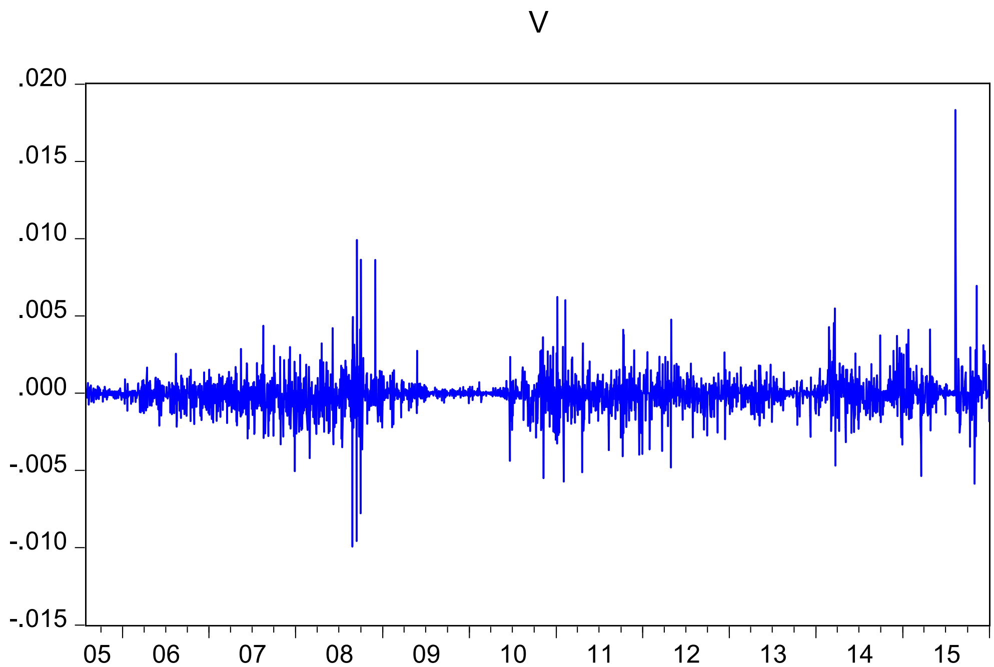

Figure 5. RMB Spot Exchange Rate Fluctuation

From the chart above, it clearly exhibits the characteristic of volatility clustering. In some time periods, the volatility is high; yet in some other time periods, the volatility is low. Large changes in the exchange rate tend to cluster together, for example, the fluctuation from June 08 to December 08. While small changes in exchange rate tend to cluster together, for example, the volatility from June 13 to December 13. Since the time series exists the volatility clustering, as can be observed in the chart of its changes dynamic, it appears that the underlying volatility heteroskedastic.

c. Stationary Test

When we research on the time series, the statistics relies on the assumption that the series is stationary, i.e., it has statistical properties that do not change with time. Formally, a time series is stationary when its mean and variance are constant over time, and the covariance between two values from the series relies only on the length of time separating the two values, not on the actual times at which the variables are observed.

The unit root test is the most popular test for examining whether a time series y_t is stationary or not using an autoregressive model. In general, for a time series $y_t = TD_t + z_t + \varepsilon_t$, where TD_t is the deterministic component, ε_t is the stationary error or residual process, and z_t is the stochastic component, the unit root test is to examine whether the stochastic component contains a unit root. Otherwise it is stationary. In large samples, augmented Dickey-Fuller test (ADF) is a commonly used test.

In this thesis research, the EViews is employed to conduct the unit root test.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.544538	0.0070
Test critical values:	1% level	-3.432565	
	5% level	-2.862404	
	10% level	-2.567275	

Table 1. Unit Root Test Result

From the ADF test result, we get that, the null hypothesis of a unit root will be rejected at the 99 percent level. So there is no unit root for the data. The series of daily USD/CNY exchange rate is stationary.

d. Choose AR (1) Model

From the previous discussion, we know that the equation of AR (1) time series is like:

$y_t = \beta y_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2)$,

After running the exchange rate data through EViews, we can observe that the shape of the correlogram of the exchange rate data would be like:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.999	0.999	2717.2	0.000
		2	0.998	0.009	5430.6	0.000
		3	0.997	-0.002	8140.4	0.000
		4	0.996	-0.005	10846.	0.000
		5	0.996	-0.000	13548.	0.000
		6	0.995	-0.009	16247.	0.000
		7	0.994	0.004	18941.	0.000
		8	0.993	-0.002	21632.	0.000
		9	0.992	0.005	24319.	0.000
		10	0.991	-0.005	27002.	0.000
		11	0.990	-0.002	29681.	0.000
		12	0.989	-0.004	32356.	0.000
		13	0.988	-0.005	35027.	0.000
		14	0.988	-0.001	37695.	0.000
		15	0.987	-0.003	40358.	0.000
		16	0.986	-0.007	43018.	0.000
		17	0.985	-0.000	45673.	0.000
		18	0.984	-0.004	48325.	0.000
		19	0.983	-0.002	50972.	0.000
		20	0.982	-0.006	53615.	0.000
		21	0.981	-0.005	56254.	0.000
		22	0.980	-0.002	58889.	0.000
		23	0.979	-0.007	61520.	0.000
		24	0.978	0.006	64147.	0.000
		25	0.977	-0.002	66769.	0.000
		26	0.976	-0.007	69387.	0.000
		27	0.975	0.002	72001.	0.000
		28	0.974	-0.005	74611.	0.000
		29	0.973	-0.004	77217.	0.000
		30	0.972	-0.002	79818.	0.000
		31	0.971	-0.002	82415.	0.000
		32	0.970	-0.001	85007.	0.000
		33	0.969	0.001	87596.	0.000
		34	0.968	-0.004	90180.	0.000
		35	0.967	0.004	92760.	0.000
		36	0.966	-0.007	95335.	0.000

Figure 6. Correlogram of RMB Exchange Rate

Autocorrelation (AC) represents the degree of similarity between a time series y_t and its lagged term. AC at lag p is the correlation coefficient for values of the time series p periods apart. Specifically, if the AC dies off more or less geometrically with increasing lag p, it means that the time series follows a low-order AR process. While, if the AC drops off to zero after a small number of lags, it means that the time series obeys a moving-average (MA) process.

The partial autocorrelation (PAC) is the correlation between two known variables (under the assumption), by taking into account some other set of variables' values. PAC at lag p is the regression coefficient on y_{t-p} when y_t is regressed on a constant. In contrast to the autocorrelation, whose pattern can be captured by an autoregression of order less than p, the partial autocorrelation at lag p will be close to zero. Specifically, the partial autocorrelation of AR (p) is very close to 0 at lag $(p+1)$. So if the PAC cuts off at lag p, then the time series is a pure AR process of order p. While if the PAC dies off gradually to zero, then the time series is a pure MA process.

Therefore, from the correlogram above, we can observe that the partial correlation cuts off at lag 1, which means it is a pure autoregressive process of order 1. So we choose AR (1) to be the fitted model for the time series of RMB to USD exchange rate.

Based on the analysis above, we input the exchange rate data and specify the AR (1) equation, and then the estimation output is displayed below:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.261055	1.087879	6.674505	0.0000
AR(1)	0.999952	0.000686	1458.155	0.0000
SIGMASQ	6.36E-05	4.81E-07	132.3753	0.0000

R-squared	0.999845	Mean dependent var	6.802746
Adjusted R-squared	0.999845	S.D. dependent var	0.640316
S.E. of regression	0.007981	Akaike info criterion	-6.819054
Sum squared resid	0.172991	Schwarz criterion	-6.812536
Log likelihood	9273.504	Hannan-Quinn criter.	-6.816698
F-statistic	8746782.	Durbin-Watson stat	2.141182
Prob(F-statistic)	0.000000		

Table 2. AR (1) Model Result

Based on the estimation output, the coefficient of AR (1) is 0.999952 and the coefficient of the constant is 7.261055. Then the AR (1) model equation would be:

$$y_t = 0.999952 y_{t-1} + 7.261055$$

e. ARCH-LM Test

In many financial time series, the magnitude of current residual appears to be related to the magnitude of recent residuals. Ignoring ARCH effect in the residuals may result in the loss of efficiency. So usually we need to examine the ARCH effect when we try to build a best fitting model. A commonly used test to examine the existence of ARCH in residuals is Lagrange Multiplier (LM) test, proposed by Engle (1982).

First, one estimates the fitted AR model, like: $y_t = \beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p} + \varepsilon_t$. Then, one obtains ε^2 and regresses them on a constant α_0 and p lagged values: $\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2$. The null hypothesis of the non-existence of ARCH is that the coefficients $\alpha_1, \alpha_2, ..., \alpha_p$ are zero. If the test rejects the null hypothesis, that is, if at least one coefficient is significant, then the residuals series exists the ARCH effect. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Obs*R-squared, which is calculated as the number of observations times R^2 from the test regression, is the LM test statistic. The LM test statistic follows χ^2 distribution with p degrees of freedom.

Based on the AR (1) model we have already built, we take the ARCH-LM test using EViews. The table below shows the result of this test:

lag	1	2	3	4	6	8
Obs*R-squared	213.0201	216.4459	217.942	218.027	219.3002	219.3087
Probability	0	0	0	0	0	0

Table 3. ARCH-LM Test Results of AR (1)

All the probabilities are 0 in these lags with large LM test statistics. So the LM test statistics are greater than the Chi-square table value. Then we reject the null hypothesis and conclude that there exists an ARCH effect in the time series.

In order to eliminate the ARCH effect, now we consider to build the GARCH model.

f. Build GARCH (1, 1)

Generally speaking, GARCH (1, 1) process is enough to capture the volatility clustering of a time series. Thus, researchers seldom use higher levels of GARCH model, but commonly choose GARCH (1, 1) to model the time series. Here, the estimation output of the GARCH (1, 1) model displays below:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.611089	0.739510	7.587572	0.0000
AR(1)	0.999601	0.000234	4269.183	0.0000
		Variance Equation		
C	1.66E-05	7.60E-07	21.89207	0.0000
RESID(-1)^2	0.329771	0.019737	16.70786	0.0000
GARCH(-1)	0.454534	0.024718	18.38898	0.0000

R-squared	0.999846	Mean dependent var	6.802267
Adjusted R-squared	0.999846	S.D. dependent var	0.639947
S.E. of regression	0.007946	Akaike info criterion	-7.046119
Sum squared resid	0.171472	Schwarz criterion	-7.035252
Log likelihood	9580.676	Hannan-Quinn criter.	-7.042191
Durbin-Watson stat	2.158844		

Table 4. GARCH (1, 1) Model Result

Based on the GARCH (1, 1) model, we firstly take the ARCH-LM test, to examine the existence of ARCH effect in the residuals. The chart below shows the result of ARCH-LM test of the GARCH (1, 1):

lag	1	2	3	4	6	8
Obs*R-squared	0.000258	0.029312	0.049011	0.122265	0.135903	0.148170
Probability	0.9872	0.9855	0.9972	0.9982	1.0000	1.0000

Table 5. ARCH-LM Test Results of GARCH (1, 1)

From the ARCH-LM test result, and from the table value of χ^2 distribution, we find that the LM test statistics are smaller than the Chi-square table value. So we accept the null hypothesis and conclude that the GARCH (1, 1) eliminates the ARCH effect.

In fact, from the Actual Fitted and Residual graph below, we can observe that the actual and fitted lines are in excellent agreement, which shows that the GARCH (1, 1) model fits the exchange rate volatility well.

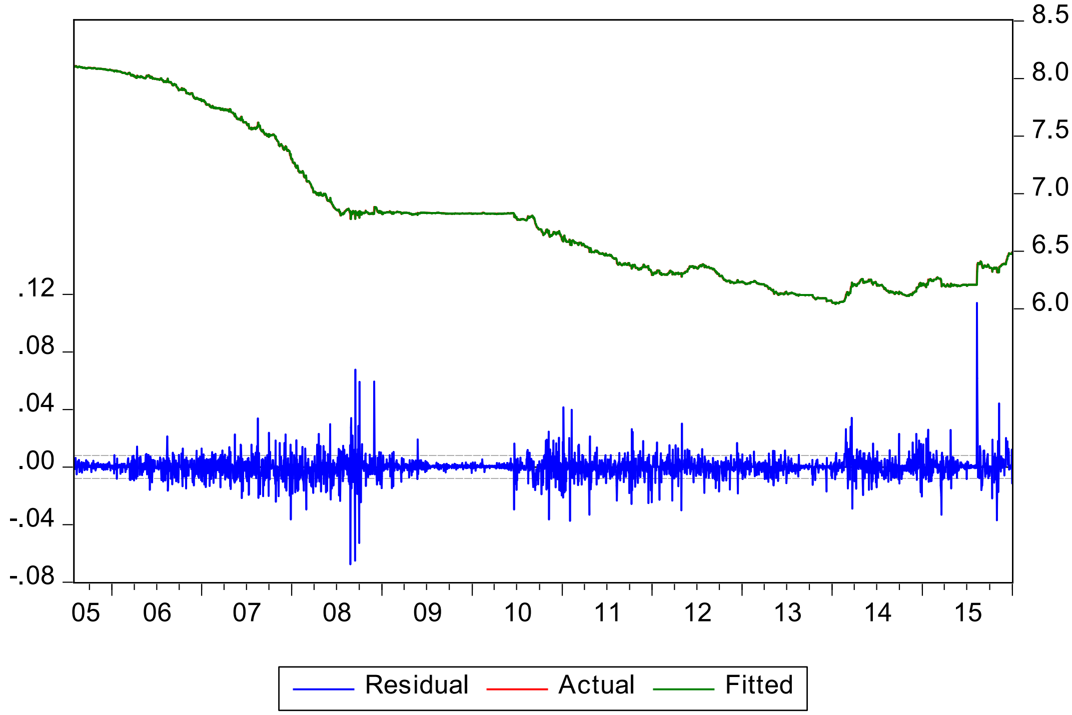

Figure 7. GARCH (1, 1) Actual Fitted and Residuals Graph

The variance equation of GARCH (1, 1) is like: $\sigma_t^2 = w + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$. When the coefficient of ε_{t-1}^2, α, is greater than zero, it means it does affect the volatility. When the coefficient of σ_{t-1}^2, β, is always greater than 0 and less than 1, it means the volatility has a long memory. And the bigger β means the longer memory.

Here from the GARCH (1, 1) result, we have the coefficient of ε_{t-1}^2 being 0.329771, which is greater than 0. So it does affect the exchange rate volatility. Also, the coefficient of σ_{t-1}^2 is 0.454534, which is less than 1. So the exchange rate volatility has a long memory property.

g. Add Dummy Variables

From July 2005 to December 2015, the People's Bank of China adjusted the RMB exchange rate fluctuation band six times. Based on these changes of the fluctuation band, this work divides the time range of the series into 6 periods, and also adds five dummy variables related to the respective periods. During the Financial Crisis period, the PBOC again pegged the RMB to the USD, which means that China fixed the RMB to USD exchange rate during the financial crisis period. Thus during that period, the RMB exchange rate volatility is 0.

Rewrite the equation of the time series after adding the dummy variables:

$$y_t = by_{t-1} + \gamma_1 d_1 y_{t-1} + \ldots + \gamma_5 d_5 y_{t-1} + \varepsilon_t$$

Where $d_1, \ldots, d_5$ are dummy variables; $\gamma_1, \ldots, \gamma_5$ are coefficients of the dummy variables respectively.

	Date	Fluctuation Band	d1	d2	d3	d4	d5
First Period	8/1/2005 - 5/1/2007	0.3%	1	0	0	0	0
Second Period	6/1/2007 - 12/1/2008	0.5%	0	1	0	0	0
FinancialCrisis	1/1/2009 - 6/1/2010	0	0	0	0	0	0
Third Period	7/1/2010 - 4/1/2012	0.5%	0	0	1	0	0
Fourth Period	4/2/2012 - 3/1/2014	1%	0	0	0	1	0

Fifth Period	3/2/2014 - 12/1/2015	2%	0	0	0	0	1

Table 6. Dummy Variables Tables

Using these code below, we generate five time series of the respective time range. Then we add the five dummy variables d_1, d_2, d_3, d_4, d_5 into the data:

```
d1=@recode(@date>@dateval("2005/07/31")and @date<@dateval("2007/05/02"),1,0)
d2=@recode(@date>@dateval("2007/05/31")and @date<@dateval("2008/12/02"),1,0)
d3=@recode(@date>@dateval("2010/06/30")and @date<@dateval("2012/04/02"),1,0)
d4=@recode(@date>@dateval("2012/04/01")and @date<@dateval("2014/03/02"),1,0)
d5=@recode(@date>@dateval("2014/03/01")and @date<@dateval("2015/12/02"),1,0)
```

The chart below shows the results after adding five dummy variables:

	Coefficient	Prob.
b	0.938517	0.0000
γ_1	0.001631	0.0000
γ_2	0.002011	0.0000
γ_3	0.002496	0.0000
γ_4	0.001878	0.0000
γ_5	0.005465	0.0000
w	1.08E-07	0.0022
α	0.111604	0.0000
β	0.405206	0.0000

Table 7. GARCH (1, 1) Model with Dummy Variables Result

Then we need to compare the original GARCH (1, 1) and the new GARCH (1, 1) with dummy variables, to see which model is better fitted. Usually we use the Akaike information criterion (AIC), Schwarz criterion (SC), and Log likelihood as the measurements for model selection.

$$AIC = \log\left(\frac{\sum_{t=1}^{T}\varepsilon_t^2}{T}\right) + \frac{2p}{T}, SC = \log\left(\frac{\sum_{t=1}^{T}\varepsilon_t^2}{T}\right) + \frac{p\log T}{T}$$

Where T is sample size, ε_t^2 is residual, p is the biggest lag.

In other word, the model with a lower AIC and lower SC and higher Log likelihood is preferred. The chart below compares the three criterion of the GARCH model without dummies and the GARCH model without dummies:

	AIC	SC	Log likelihood
GARCH w/o dummies	-7.046119	-7.035252	9580.676
GARCH w/ dummies	-7.208292	-7.186557	9806.069

Table 8. AIC SC Log-Likelihood Results

Compared to the GARCH (1, 1) without dummy variables, the GARCH (1, 1) with dummy variables has smaller AIC and SC, and a bigger log likelihood. Thus, the adjusted GARCH model based on the widening fluctuation band of exchange rate can fit the exchange rate dynamic better.

In addition, from the GARCH (1, 1) model with dummy variables result, we get the coefficient of ε_{t-1}^2 is 0.111604, which is greater than 0. So it also does affect the exchange rate volatility. And, the coefficient of δ_{t-1}^2 is 0.913934, which is highly significant. So the exchange rate volatility has a long memory property. Besides, the dummy variables coefficient can exhibit the effects of the fluctuation band changes on the RMB exchange rate volatility. Since the coefficients of five dummy are 0.001631, 0.002011, 0.002496, 0.001878, 0.005465 respectively, so the widening of the fluctuation band of exchange rate does affect the volatility in the five periods.

CHAPTER 4

CONCLUSION

The widening of the fluctuation band of the RMB exchange rate does affect the volatility of exchange rate. The GARCH model can fit the RMB exchange rate volatility well. We can observe the volatility clustering of the exchange rate from the graph generated in the GARCH model. By adding the dummy variables based on the widening of fluctuation bands in different periods, the GARCH model fits the exchange rate volatility better, with the five dummy variables being 0.001631, 0.002011, 0.002496, 0.001878, 0.005465. So the widening of fluctuation band does affect the exchange rate volatility in the five periods.

From the observation of China's economy development during the past ten year, the relatively flexible exchange rate helps the economy growth and promotes a deeper participation in the global market. China has realized the necessity of adopting the floated exchange rate, and is implementing the transition to the fully flexible exchange rate. Widening the fluctuation bands several times during the past ten year is a signal, and affects the RMB exchange rate volatility constantly. In our opinion, so far, keeping widening the fluctuation band constantly might be a good choice for the RMB exchange rate.

REFERENCES

(1) Robert Engle, “GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics”. *Journal of Economic Perspective--Volume 15,* Fall 2001, Page 157-168

(2) Chad Crawford Salitan (2010). “China’s Currency Regime: The Perceived Threat to the U.S. Economy”.

(3) Maiden Voyage (2015). “The yuan joins the SDR: Reserve-currency status might make for a weaker yuan”. *The Economists*, Dec 5th 2015

(4) “IMF’s Executive Board Completes Review of SDR Basket, Includes Chinese Renminbi”. *International Monetary Fund*, Press Release No. 15/540, November30, 2015

(5) Elvis Picardo, CFA, (2014). “Why China's Currency Tangos With the USD”. *Investopedia*, March 14, 2014

(6) Lingling Wei (2014). “China Allows Wider Currency Fluctuation: Central Bank Move Seen as Step Toward Establishing Market-Based Exchange-Rate”. *The Walls Street Journal*, March 15, 2014

(7) Shiv Mehta, CFA (2015). “Chinese Yuan: A 360 Degree Analysis (CNY)”. I*nvestopedia*, August 20, 2015

(8) Ruey, Tsay S. (2005). “Analysis of Financial Time Series”.

(9) Melvin, Michael, Lukas menhoff, Maik Schmeling (2009). “Exchange Rate Management in Emerging Markets”. J*ournal of International Economics,* Vol.79, Sep. PP54-63

(10) Bollerslev T. (1986). “Generalized Autoregressive Conditional Heteroskedasticity”. *Journal of Econometrics*, Vol.31, 307-324

(11) Bartolini, Leonardo, Alessandro Prati (1990). “Soft Exchange Rate Bands and Speculative Attacks: Theory, and Evidence from the Erm since August 1993”. J*ournal of International Economics*, Vol.49 PP1-29

(12) Rama Cont (2005). “Volatility Clustering in Financial Markets: Empirical Facts and Agent-Based Models”.

(13) Suliman Zakaria Suliman Abdalla (2012). “Modeling Exchange Rate Volatility using GARCH Models: Empirical Evidence from Arab Countries”. *International Journal of Economics and Finance,* Vol. 4, No. 3; March 2012

(14) Petra Posede (2005) “Properties and Estimation of GARCH (1, 1) Model”. *Metodoloˇski zvezki,* Vol. 2, No. 2, 2005, 243-257

(15) Ashima Goyal, Sanchit Arora (2010) “A GARCH Analysis of Exchange Rate Volatility and the Effectiveness of Central Bank Actions”.

(16) Deniz Erdemlioglu, Sébastien Laurent, Christopher J. Neely (2012). “Econometric Modeling of Exchange Rate Volatility and Jumps”. *Federal Reserve Bank of St. Louis Working Paper Series, 2012-008A*

(17) John Dukich, Kyung Yong Kim, Huan-Hsun Lin (2010). “Modeling Exchange Rates using the GARCH Model”.

APPENDIX

Chi-Square Probability Table

df	0.995	0.99	0.975	0.95	0.9	0.1	0.05	0.025	0.01	0.005
1	---	---	0.001	0.004	0.016	2.706	3.841	5.024	6.635	7.879
2	0.01	0.02	0.051	0.103	0.211	4.605	5.991	7.378	9.21	10.597
3	0.072	0.115	0.216	0.352	0.584	6.251	7.815	9.348	11.345	12.838
4	0.207	0.297	0.484	0.711	1.064	7.779	9.488	11.143	13.277	14.86
5	0.412	0.554	0.831	1.145	1.61	9.236	11.07	12.833	15.086	16.75
6	0.676	0.872	1.237	1.635	2.204	10.645	12.592	14.449	16.812	18.548
7	0.989	1.239	1.69	2.167	2.833	12.017	14.067	16.013	18.475	20.278
8	1.344	1.646	2.18	2.733	3.49	13.362	15.507	17.535	20.09	21.955
9	1.735	2.088	2.7	3.325	4.168	14.684	16.919	19.023	21.666	23.589
10	2.156	2.558	3.247	3.94	4.865	15.987	18.307	20.483	23.209	25.188
11	2.603	3.053	3.816	4.575	5.578	17.275	19.675	21.92	24.725	26.757
12	3.074	3.571	4.404	5.226	6.304	18.549	21.026	23.337	26.217	28.3
13	3.565	4.107	5.009	5.892	7.042	19.812	22.362	24.736	27.688	29.819
14	4.075	4.66	5.629	6.571	7.79	21.064	23.685	26.119	29.141	31.319
15	4.601	5.229	6.262	7.261	8.547	22.307	24.996	27.488	30.578	32.801
16	5.142	5.812	6.908	7.962	9.312	23.542	26.296	28.845	32	34.267
17	5.697	6.408	7.564	8.672	10.085	24.769	27.587	30.191	33.409	35.718
18	6.265	7.015	8.231	9.39	10.865	25.989	28.869	31.526	34.805	37.156
19	6.844	7.633	8.907	10.117	11.651	27.204	30.144	32.852	36.191	38.582
20	7.434	8.26	9.591	10.851	12.443	28.412	31.41	34.17	37.566	39.997
21	8.034	8.897	10.283	11.591	13.24	29.615	32.671	35.479	38.932	41.401
22	8.643	9.542	10.982	12.338	14.041	30.813	33.924	36.781	40.289	42.796
23	9.26	10.196	11.689	13.091	14.848	32.007	35.172	38.076	41.638	44.181
24	9.886	10.856	12.401	13.848	15.659	33.196	36.415	39.364	42.98	45.559
25	10.52	11.524	13.12	14.611	16.473	34.382	37.652	40.646	44.314	46.928
26	11.16	12.198	13.844	15.379	17.292	35.563	38.885	41.923	45.642	48.29
27	11.808	12.879	14.573	16.151	18.114	36.741	40.113	43.195	46.963	49.645
28	12.461	13.565	15.308	16.928	18.939	37.916	41.337	44.461	48.278	50.993
29	13.121	14.256	16.047	17.708	19.768	39.087	42.557	45.722	49.588	52.336
30	13.787	14.953	16.791	18.493	20.599	40.256	43.773	46.979	50.892	53.672
40	20.707	22.164	24.433	26.509	29.051	51.805	55.758	59.342	63.691	66.766
50	27.991	29.707	32.357	34.764	37.689	63.167	67.505	71.42	76.154	79.49
60	35.534	37.485	40.482	43.188	46.459	74.397	79.082	83.298	88.379	91.952
70	43.275	45.442	48.758	51.739	55.329	85.527	90.531	95.023	100.425	104.215
80	51.172	53.54	57.153	60.391	64.278	96.578	101.879	106.629	112.329	116.321
90	59.196	61.754	65.647	69.126	73.291	107.565	113.145	118.136	124.116	128.299
100	67.328	70.065	74.222	77.929	82.358	118.498	124.342	129.561	135.807	140.169