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VOLATILITY OF CHINA SHANGHAI STOCK PRICE-EXCHANGE RATE

Ming Fan [a], Mengmeng Dong [b]
[a] National University of Malaysia, Malaysia
[b] Hangzhou Wanxiang Polytechnic, China
Corresponding email: 674279825@qq.com

Abstract

This paper examines the use of GARCH-type models for modelling volatility and explaining relationship between stock market risk and exchange rate risk in CHINA. We use daily data from China Shanghai A Stock Price and Exchange Rate. Various time series methods are employed, including the simple GARCH model, as well as exponential GARCH, threshold GARCH. We find strong evidence that daily returns can be characterised by the above models. For both markets, we conclude that the best model is GARCH (1,1)and the asymmetric effect is not significant. These findings are strongly recommended to financial managers and modellers dealing with international markets.

Keywords: China Stock Markets, Exchange Rate, GARCH &Volatility.

1. Introduction

On July 21, 2005, the People's Bank of China announced that the RMB exchange rate was no longer a single pegged to the US dollar, but with reference to a basket of currencies to implement a managed floating exchange rate system. Since then, China's exchange rate system has entered a relatively floating state from a relatively fixed state, and the impact of exchange rate fluctuations on other parts of the financial market (the stock market) is becoming more and more significant. Stock market and the foreign exchange market are two important parts of the financial market. Their coordinated development is directly related to the steady development of financial market. Therefore, it is of great theoretical and practical significance to deeply study the relationship between RMB exchange rate fluctuation and Chinese stock price remuneration during this period. The second part is the literature review. The third part is the empirical analysis of the relationship between RMB exchange rate volatility and Chinese stock price reward. The fourth part is the empirical analysis. The result analysis and the explanation; The fifth part is the conclusion and the suggestion.

2. Literature Reviews

For the theoretical aspect, the current theories on the relationship between exchange rates and stock prices are: the flow-oriented model and the balance-of-securities theory. The flow-oriented model (Dornbusch and Fisher, 1980) emphasizes the current account or trade balance and the relationship between stock prices is uncertain. The theory of portfolio balance (Branson and Henderson, 1985) argues that, under other conditions, the holder of securities will compare the returns on various securities investments and decide whether the holdings of the securities held Proportionately, investors will hold a higher proportion of higher-paid assets and lower holdings of lower-paid assets, believing that exchange rate volatility (direct price method) is inversely related to stock price returns He and Ng (1998) take Japan's stock price as a sample to explore

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whether there is exchange rate risk in the stock price reward, the research results show that the Japanese company's share price returns include the risk of exchange rate risk, there is a correlation between exchange rate and stock price APET, P.G (2001) empirical research on the relationship between exchange rate and stock markets in India shows that there is no Granger causality relationship between exchange rate and stock market.

3. Data

The sample data of this paper is from January 2, 2004 to November 30, 2016, the Chinese stock price returns and RMB to the US dollar nominal exchange rate data for empirical research. The data are from the website of the State Administration of Foreign Exchange (SAFE), which is omitted in this paper because of the large size of the data. The data includes two parts: the exchange rate data and the Shanghai Composite Index data, the exchange rate refers to the People's Bank of China announced the RMB against the US dollar exchange rate (central parity) daily data; stock index is the Shanghai Composite Index, the index opening, Closing price of the highest and lowest points, the most representative of the closing price, so the daily index of the Shanghai Composite Index closed as the representative of stock price returns. In terms of data processing, since China's stock exchanges do not operate on holidays, the exchange rate data at the same time will be deleted when the stock market is closed to meet the common trading days in the stock and exchange markets.

The exchange rate of China against the U.S. dollar means that how many units of RMB to buy one unit of U.S. dollar. The data we used here is the daily statistical record (see figure 1,2).

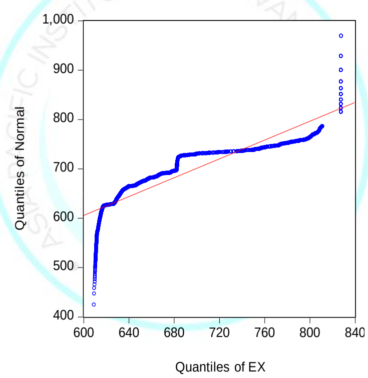

Figure 1: QQ-PLOT of the daily change of exchange rate

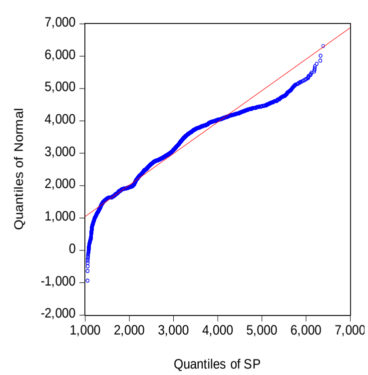

Figure 2: QQ-PLOT of the daily StockPrice

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For further confirmation of this guess, ADF test is necessary (see Table 1).

Table 1: ADF test

Variable	**ADF**			
	Level	P-Value	First Difference	P-Value
rsp	-1.813405	0.3743	-54.76857	0.0001
rex	-2.705424	0.0731	-51.58789	0.0001

4. Methodology

In financial markets, fluctuation of prices (or returns) goes under the name of volatility - how much prices (or returns) are changing over a given period. Linear models are unable to explain a number of important features common to much financial data, including leptokurtosis, volatility clustering, long memory, volatility smile and leverage effects. That is, because the assumption of homoscedasticity (or constant variance) is not appropriate when using financial data, and in such instances it is preferable to examine patterns that allow the variance to depend upon its history. Therefore, to model the non-constant volatility parameter, we consider GARCH-type models. Bollerslev (1986) proposed a GARCH(p,q) random process, which can represent a greater degree of inertia in its conditional volatility or risk. Following the literature (Akgiray, 1989; Connolly, 1989; Baillie and DeGennaro,1990; Bera and Higgins, 1993; Bollerslev et al., 1992; Floros, 2007, among others), a simple GARCH model is parsimonious and gives significant results. GARCH allows the conditional variance of a stock index to be dependent upon previous own lags. The GARCH (p,q) model is given by:

$$R_t = \mu + \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where, p is the order of GARCH while q is the order of ARCH process. Error, ε_t is assumed to be normally distributed with zero mean and conditional variance, σ_t^2, R_t are returns, so we expect their mean value (μ) to be positive and small. We also expect the value of ω to be small. All parameters invariance equation must be positive, and $\alpha + \beta$ is expected to be less than, but close to, unity, with $\alpha < \beta$, News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

Financial theory suggests that an increase in variance results in a higher expected return. Toaccount for this, GARCH-in-Mean models are also considered, see Kim and Kon (1994). StandardGARCH-M model is given by:

$$R_t = \mu + \beta_2 \sigma_t^2 + \varepsilon_t$$

$$\varepsilon_t \sim N\left(0, \sigma_t^2\right)$$

$$\sigma_t^2 = \omega + a\varepsilon_{t-i}^2 + \beta_1 \sigma_{t-1}^2$$

if β_2 is positive (and significant), then increased risk leads to a rise in the mean return ($\beta_2 \sigma_t^2$ can be interpreted as a risk premium).

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Exponential-GARCH models were designed to capture the leverage effect noted in Black(1976) and French et al. (1987). A simple variance specification of EGARCH is given by:

$$\log\sigma_t^2 = \omega + \beta\log\sigma_{t-1}^2 + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential(so the variance is non-negative). The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. If $\gamma \neq 0$,then the impact is asymmetric.

Furthermore, the Threshold-GARCH model was introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The TGARCH specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i\varepsilon_{t-i}^2 + \gamma\varepsilon_{t-i}^2 d_{t-1} + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2$$

Where, d_t =1 if ε_t <0 and d_t =0 otherwise.

In this model, good news(ε_t >0)and bad news (ε_t <0) have differential effects on the conditional variance. Good news has an impact of a, while bad news has an impact of $a+\gamma$. If γ >0then the leverage effect exists and bad news increases volatility, while if $\gamma \neq 0$ the news impact is a symmetric.

5. The steps and results

5. 1Modelling

From results of the above tables, both of them are indicating that what we guessed is consistent with the testing results and time series of exchange rate is not stationary. According to the textbook, we have to convert the sequence to be stationary. Therefore, we use the return on exchange rate to measure the volatility. The equation is as follow:

$$rsp = \log(sp_t) - \log(sp_{t-1})$$

$$rex = \log(ex_t) - \log(ex_{t-1})$$

$$rsp_t = \varphi + \theta rex_t + \varepsilon_t$$

5.2 Rate of return distribution

From these graph, we can see it has higher kurtosis and fat tail , we can conclude it has arch effect. So next, we will do the arch test.

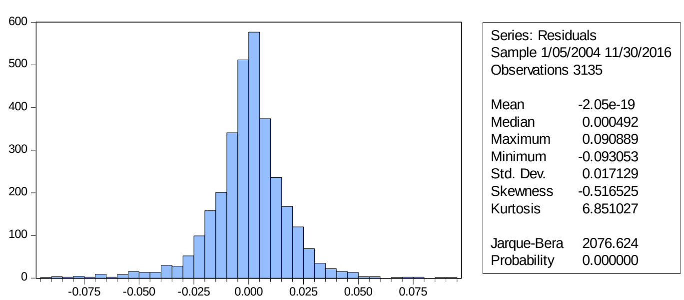

Figure3:Residual nominal distribution

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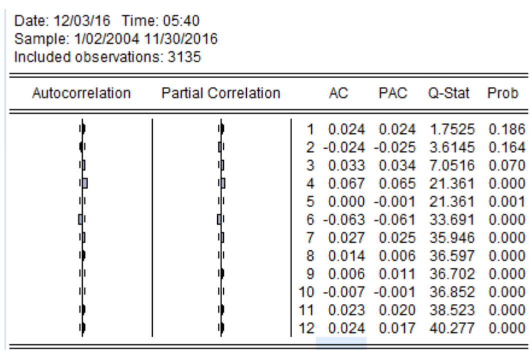
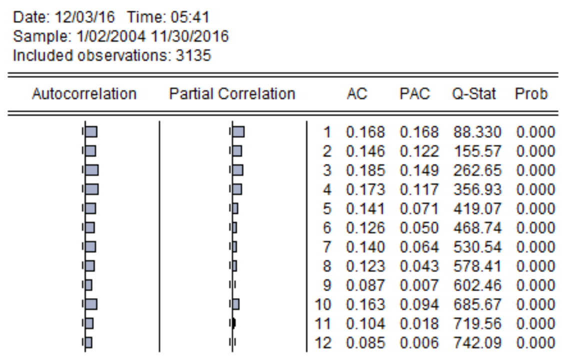
5.3 Autocorrelation Test

The ACF and PAC graph residual phase obtained by this equation are shown in Fig. 4, and the ACF and PAC OF residual square are shown in Fig 5. As can be seen from Fig. 4 and Fig. 5, residual has no obvious autocorrelation, while residual square has significant autocorrelation. This shows that there is a nonlinear relationship between the yields of different times, and the conditional variance has time variability, which proves the clustering of the volatility of the yield. From the arch-LM test （Fig 6),we can conclude it has arch effect and then we will find which model is best for our data.


Date: 12/03/16 Time: 05:40
Sample: 1/02/2004 11/30/2016
Included observations: 3135

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.024	0.024	1.7525	0.186
		2	-0.024	-0.025	3.6145	0.164
		3	0.033	0.034	7.0516	0.070
		4	0.067	0.065	21.361	0.000
		5	0.000	-0.001	21.361	0.001
		6	-0.063	-0.061	33.691	0.000
		7	0.027	0.025	35.946	0.000
		8	0.014	0.006	36.597	0.000
		9	0.006	0.011	36.702	0.000
		10	-0.007	-0.001	36.852	0.000
		11	0.023	0.020	38.523	0.000
		12	0.024	0.017	40.277	0.000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Sample: 1/02/2004 11/30/2016
Included observations: 3135

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.168	0.168	88.330	0.000
		2	0.146	0.122	155.57	0.000
		3	0.185	0.149	262.65	0.000
		4	0.173	0.117	356.93	0.000
		5	0.141	0.071	419.07	0.000
		6	0.126	0.050	468.74	0.000
		7	0.140	0.064	530.54	0.000
		8	0.123	0.043	578.41	0.000
		9	0.087	0.007	602.46	0.000
		10	0.163	0.094	685.67	0.000
		11	0.104	0.018	719.56	0.000
		12	0.085	0.006	742.09	0.000

Figure 4: ACF and PAC OF residual square   Figure 5: ACF and PAC OF residual square

Table 2: Heteroskedasticity Test: ARCH

F-statistic	**69.64035**	**Prob. F(2,3130)**	**0.0000**
Obs*R-squared	133.4747	Prob. Chi-Square(2)	0.0000

5.4 Garch Family Setup

Normally, we use two information criteria such as AIC and SC to make sure of the optimal order of Garch model. The results of different orders we used is as follow. From indications of AIC and SC, Garch(1,1) model should be the best one to estimate the conditional variance which could affect the volatility of stock price to exchange rate. Certainly, we ought to notice the LL(Log likelihood Ratio) might provide different opinions on it, but since AIC and SC put forward the agreement on choosing the optimal orders for Garch model, the convincing power of this agreement is overwhelming.

Table 3:The results of different orders we take for Garch model

(p,q)	AIC	SC	LL
(0,1)	-5.344926	-5.33526	8383.172
(1,0)	-5.345551	-5.335898	8381.478
(1,1)	-5.559106	-5.545589	8715.339
(1,2)	-5.346396	-5.332882	8384.802
(2,1)	-5.347750	-5.334230	8381.577
(2,2)	-5.348077	-5.332629	8385.763

Table 4:Garth-family Models for Volatility (Variance Specifications)

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Index/Model	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)	GARCH (1,1)-M	TGARCH (1,1) -M
ω	1.56E-06 (4.236893)	-0.341604 (-11.61796)	1.62E-06 (4.289290)	1.55E-06 (4.209821)	1.61E-06 -4.271718
α	0.056145 (12.86042)*	0.169712 (15.56592)*	0.054823 (9.760774)*	0.056097 (12.84828)*	0.054682 (9.736868) *
γ		-0.012336 (- 2.301114)*	0.003491 (0.539805)*		0.003734 -0.576862
β	0.939417 (217.6955)*	0.975207 (326.3005)*	0.938674 (216.8610)*	0.939480 (218.0221)*	0.93871 (217.2916) *
α+β	0.995562	1.144919	0.993497	0.995577	0.993392
ρ				-0.436965 (- 0.276776)*	-0.4983 (-0.314133)
AIC	-5.559106	-5.544875	-5.55852	-5.558491	-5.557912
SIC	-5.545589	-5.529431	-5.543072	-5.543043	-5.540533
ll	8715.339	8696.819	8715.421	8715.376	8715.469

Note: 1.we report the results from GARCH-TYPE models is under the assumption that the errors are conditionally normal distributed.2. Z-statistics in the parentheses.3.* significant at 5% level.4.For the individual specific estimated results of all GARCH-type models, see the appendix.

We estimate a number of different GARCH-family models to explain conditional variance and volatility clustering. Table 3 reports the parameter estimates of all conditional volatility (GARCH-family) models defined in the previous section. For both indices, besides EGARCH(1,1), α+β=1.14, which means volatility shocks are becoming larger, the other sum of GARCH family coefficients are very close to one, indicating that volatility shocks are quite persistent.

First, we see from AIC,SIC and LL index, we could get GARCH(1,1) is the best model. And we further compare between GARCH(1,1), EGARCH(1,1) and TGARCH(1,1), we could see γ is significant in EGARCH(1,1) and TGARCH(1,1) model, which means bad news has significant effects than good news in this model; and further we see the ω in these three models are not significant. Furthermore, EGARCH models show a negative and significant □□γ parameter, indicating the existence of the leverage effect in returns during the sample periods. However, the TGARCH leverage effect term is also significant in the case ,while the news impact is asymmetric

We go further compare GARCH(1,1)-M and TGARCH(1,1) –M, ω in these two models are not significant, which means the variance has no significant effect on means equation; which means these two model are not better than GARCH(1,1)

In GARCH(1,1) model, the coefficient β is especially high than the coefficient α , which indicating a long memory in the variance.

5.5 Further ARCH-LM Test

We continue to do the ARCH-LM test on the results of GARCH (1,1) to see whether there are still ARCH effects. From Figure 7 we can see that the Chi-Square (1) value is 0.42, which is far more than 0.05, so we conclude the GARCH model has no ARCH effect. We analyzed the residual residuals (see Figure 8.9), and we can see that the Heteroskedasticity distribution has been fulfilled by the student's distribution.

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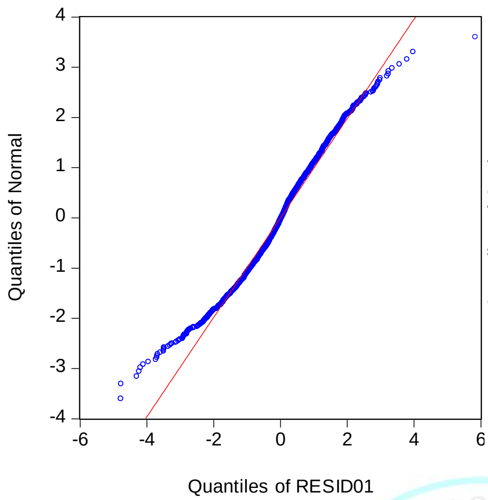
Table 2: Heteroskedasticity Test: ARCH

F-statistic	**0.638445**	**Prob. F(2,3130)**	**0.4243**
Obs*R-squared	0.638722	Prob. Chi-Square(2)	0.4242



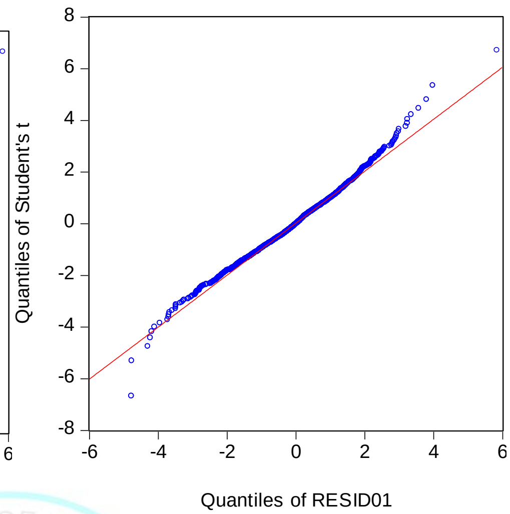


Figure8: Heteroskedasticity Test: ARCHFigure 9 Heteroskedasticity Test: ARCH

Conclusion

In Table 9, we build up 5 GARCH-type models. The lagged orders of both in mean equation is selected by the SC, AIC and LL which are same as what we mentioned above. In addition, since we have already diagnosed that the residual of returns is not normally distributed, we assume that it is demonstrated by student'T distribution.

Table 10 reports the each estimated parameter of every GARCH-family models to explain conditional variance and volatility clustering. We should notice that the sums of α and β of only GARCH model and Garch-M model we test here are close to 1, indicating that the volatility shocks affecting variance would be persistent. Others are either more than 1, or both of coefficients less than 0, which are not qualify the requirements of stationary sequences.

In GARCH(1,1)-M model, the coefficient of the conditional variance in the mean equation, denoted as ρ, is equal to -0.436965 which is significantly negative. It indicates that there is a relationship between variance and returns of stock price, in other words, one unit increase in forecasting risk will bring 0.43 unit decrease in return on stock price.
Furthermore, EGARCH, TGARCH, models all indicate that there is asymmetric effects in volatility shocks, even though all of them are not appropriate to be the best Garch model. It still means that leverage effects are existing.

Finally, the mean values of the volatility (GARCH variance series) from the above GARCH models are 1.56E-06 (variables in form of logarithm in all mean equations).

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