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Empirical Research on Shanghai Stock Index Based on GARCH Model

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Abstract: The stock market has been affected by many factors, leading to the stock market is unpredictable, which makes stocks have high-risk and high-yield characteristics. Studying the stock market's Shanghai stock Index is the key to reducing risks and increasing profits. This article analyzes the characteristics of the daily yield series by collecting the daily closing price of the Shanghai stock Index from the daily closing price of June 3, 2013 to June 29, 2018, and using Eviews statistical analysis software to analyse the nature of the sequence, the time series model GARCH(1,1) is initially fitted. The empirical results show that the GARCH(1,1) model has a good fitting effect on the time series of the logarithmic price of the Shanghai Stock Index.

Keywords: GARCH model, Shanghai stock index, volatility

I. Introduction

In the past ten years, China's stock market has experienced ups and downs, and the volatility is far greater than that of developed countries such as Europe and the United States. There are large fluctuations and irrational bubbles in the stock market. The People's bank of China needs to adopt monetary or fiscal policies in time to regulate the stock market. For example, the impact of the global financial crisis in 2008 on the world economy is far-reaching, leading to the bursting of the Chinese stock market bubble, China's stock market continued to fall, market confidence is low, and the national economy is in recession. Therefore, for the gold rushers in the stock market, it is quite necessary to study the stock price fluctuation trend. The stock index is the leading indicator of the macro economy. The Shanghai Stock Index is an important reference indicator for China's stock market and can reflect stocks in a timely and sensitive manner. The fluctuation of the market, so the Shanghai Composite Index can be regarded as a barometer of the changes in China's stock market, we can study the factors affecting the current stock price index from the perspective of the Shanghai Composite Index.

Most studies have shown that financial time series have volatility clusters (Mandelbrot, 1963), spikes and thick tails, and leverage effects. Foreign research on the volatility of stock market prices has a long history. As early as the 1960s, Fama (1965) observed changes in speculative prices and changes in yields with stable periods and variable periods. The price fluctuations are clustered, and the variance changes with time. Subsequently, foreign countries have conducted a lot of research on the characteristics of speculative price fluctuations. The most successful of these is the autoregressive conditional heteroscedasticity model proposed by Engle (1982), the ARCH model and its extended model. These ARCH models are widely used in the research of stock market, currency market, foreign exchange market and futures market to describe the volatility characteristics of financial time series such as stock price, interest rate, exchange rate and futures price. Bollerslev (1986) proposed the GARCH model after the ARCH model proposed by Engle to further model the variance of the error and conveniently describe the high-order ARCH process, so it is more suitable for the empirical study of time series. Through the efforts of many researchers, based on the GARCH model, a large family of large GARCH models has been developed. These models have become the most commonly used tools for empirical research to measure volatility and profitability.

The Chinese stock market started relatively late compared with the foreign stock market. The domestic scholars' research on the GARCH model of the Chinese stock market is still being explored and improved. It is very important to do some researches on the price volatility of the securities market by using the GARCH model is the GARCH model in the securities market., including the GARCH effect test for stock market price volatility. Mr. Changfeng Wu (1999) [1] used the regression GARCH model to conduct a preliminary analysis of China's Shanghai and Shenzhen stock markets. The results show that the fluctuations of the two index yields, that is, the conditional variance series, have long memory characteristics and cluster characteristics. Mr. Chaolong Yue (2001) [2] used the GARCH model to empirically analyze the Shanghai stock market's return rate, pointing out that the Shanghai stock market's return rate has not only the conditional heteroscedasticity but also the leverage effect.

This article analyzes the Shanghai Stock Index by using the latest data of the Shanghai Stock Index. It is time-sensitive and provides a simple empirical analysis of the data. It tests the volatility of the sequence and whether there is heteroscedasticity in the sequence. Finally, the data is built using the random walk model., get the optimal GARCH model.

II. Empirical analysis

1. Briefly describe the model

ARCH(q) model:

$$\varepsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2)$$

$$\varepsilon_t = z_t \sigma_t, z_t \text{ is iid, and} E(z_t) = 0, Var(z_t) = 1$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

among them, ε_t Sequence is independent, ψ_{t-1} is the set of information obtained for the t-1 period, σ_t^2 is the conditional variance of ε_t, $\alpha_0>0$, $\alpha_i \geq 0$ (i=1,2,⋯,q)

The core idea of the ARCH model is that the variance of the residual at time T depends on the magnitude of the residual square of time T-1. Therefore, in the ARCH model, two core model regression processes are involved, namely the original regression model (often called the conditional mean regression model or the mean variance equation) and the regression regression model (often referred to as the heteroscedastic regression model or variance). equation).

In 1986, Bollerslev proposed an extended model based on the ARCH(q) model: the GARCH(p,q) model, which transformed the final step of the ARCH model into:

$$\sigma_1^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j}^2$$

Where $p \geq 0$, $q>0$, $\alpha_0 > 0$, $\alpha_i \geq 0$ (i=1,⋯,q) , $\beta_j \geq 0$ (j=1,…,p)

The basic idea of the GARCH model is that the conditional variance σ_t^2 of the disturbance term ε_t, relying on the previous value of the perturbation term itself $\varepsilon_{t-1}, \varepsilon_{t-2}$, ...and the previous value of the conditional variance $\sigma_{t-1}^2, \sigma_{t-2}^2$, ... At the same time, when p=0, the GARCH(p,q) model is the ARCH(q) model. Therefore, the ARCH(q) model is a special case of the GARCH model. It also has the characteristics of the ARCH(q) model and can simulate the cluster phenomenon of price fluctuations.

In order to capture the leverage of financial time series, Nelson proposed the index GARCH (exponential GARCH) in 1991, which is a model derived from GARCH. Soon afterwards Zakaran (1990) and Glosten, Jaganathan and Runkle (1994) proposed a threshold ARCH model (TGARCH model).

2. Figures and Tables

2.1 Stationarity test

Let p denote the closing price of the stock and lp denote the stock return. This article takes the data of China's Shanghai Stock Exchange Index in recent years as the research object, and selects the total closing price of the Shanghai Composite Index from June 3, 2013 to June 29, 2018. The sample data is imported into Eviews7.0, and the corresponding line chart (shown in Figure 1) is made. As can be seen from Figure 1, p is obviously non-stationary. (The horizontal axis represents the number of sample data, and the vertical axis represents the corresponding closing price)

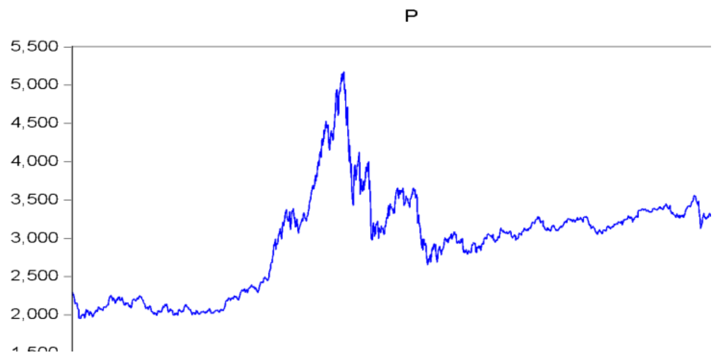

Figure 1Line chart of raw data

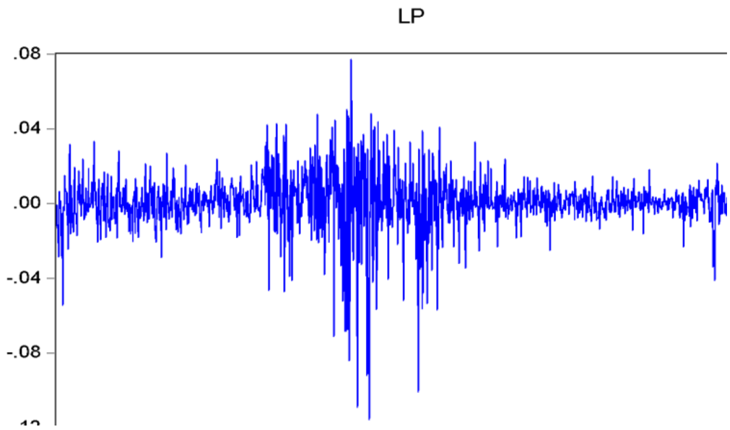

Figure 2Daily rate of return line chart

Using the formula "$lp_t = log(p_t) - log(p_{t-1})$"to converte the original closing price data into a rate of return and make a line graph of the rate of return (shown in Figure 2). From the figure we can see that the stock yield series lp has obvious clustering, that is, the stock daily yield fluctuates sharply after a large fluctuation.

To further verify the smoothness of the transformed data, we can perform a unit root test on the data as follows:

Table 1Unit root test of daily yield

Null Hypothesis: LP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.30410	0.0000
Test critical values:	1% level	-3.435432	
	5% level	-2.863672	
	10% level	-2.567955	

*MacKinnon (1996) one-sided p-values.

The unit root test results are shown in Table 1. At this time, the value of ADF is -34.30410, which is much smaller than the t-statistic value at 1%, 5%, and 10% of the significant level, and its P value is 0, indicating that reject the original hypothesis that data is non-stationary., so the converted daily yield series is stable.

2.2 normality test

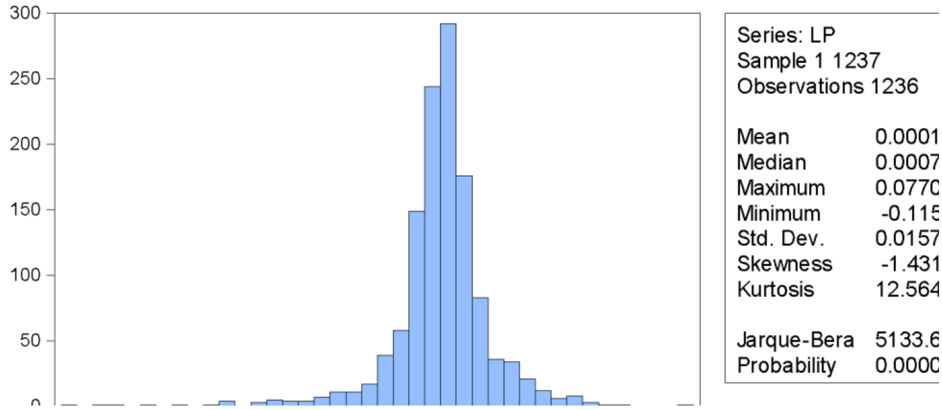

Figure 3 Normality test

According to the basic statistical data shown in Figure 3, it can be seen that the stock yield series has a sharp peak-thickness phenomenon (kurtosis = 12.56497), which is much higher than the kurtosis value of the normal distribution of 3,it shows that the yield sequence has the characteristics of spikes and thick tails. At the same time, the P value of the JB statistic is zero, and the assumption that the stock yield series obeys the normal distribution was rejected.

2.3 Relevance test

Table 2 Related tests

Date: 07/17/18 Time: 19:47
Sample: 1 1237
Included observations: 1236

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.023	0.023	0.6435	0.422
| |	| |	2	-0.029	-0.030	1.6915	0.429
| |	| |	3	-0.005	-0.004	1.7252	0.631
| |	| |	4	0.064	0.064	6.8357	0.145
| |	| |	5	0.000	-0.003	6.8357	0.233
| |	| |	6	-0.042	-0.039	9.0628	0.170
| |	| |	7	0.067	0.070	14.597	0.042
| |	| |	8	0.058	0.049	18.843	0.016
| |	| |	9	0.018	0.019	19.255	0.023
*| |	*| |	10	-0.081	-0.074	27.420	0.002
| |	| |	11	-0.033	-0.037	28.752	0.002
| |	| |	12	0.010	0.000	28.880	0.004
| |	| |	13	0.038	0.040	30.720	0.004
| |	| |	14	-0.028	-0.021	31.713	0.004
| |	| |	15	0.016	0.018	32.052	0.006
| |	| |	16	0.028	0.015	33.066	0.007
|* |	|* |	17	0.078	0.080	40.609	0.001

| |	| |	18	-0.030	-0.017	41.759	0.001
| |	| |	19	-0.025	-0.014	42.522	0.002
|* |	|* |	20	0.112	0.100	58.365	0.000

Analysising the stock return rate lp yields statistically,lp's correlation diagram and partial autocorrelation diagram are obtained (Table 2). Through correlation graph and partial autocorrelation graph , it can be seen that the autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) of the yield series have significant effects in the lag phase 10, indicating the existence of autocorrelation and partial autocorrelation.

The model was estimated using the OLS estimation method, and Table 3 was obtained.

Table 3 Least Squares Estimation Results

Dependent Variable: LP
Method: Least Squares
Date: 07/17/18 Time: 19:51
Sample (adjusted): 2 1237
Included observations: 1236 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000173	0.000448	0.385836	0.6997

R-squared	0.000000	Mean dependent var	0.000173
Adjusted R-squared	0.000000	SD dependent var	0.015764
SE of regression	0.015764	Akaike info criterion	-5.461408
Sum squared resid	0.306889	Schwarz criterion	-5.457266
Log likelihood	3376.150	Hannan-Quinn criter.	-5.459850
Durbin-Watson stat	1.952478		

According to the estimation results shown in Table 3, the intercept term is not significant at the significance level of 0.1. In order to estimate the equation better, the residual of the estimation result is observed, and it is necessary to test whether the residual sequence has conditional heteroskedasticity.

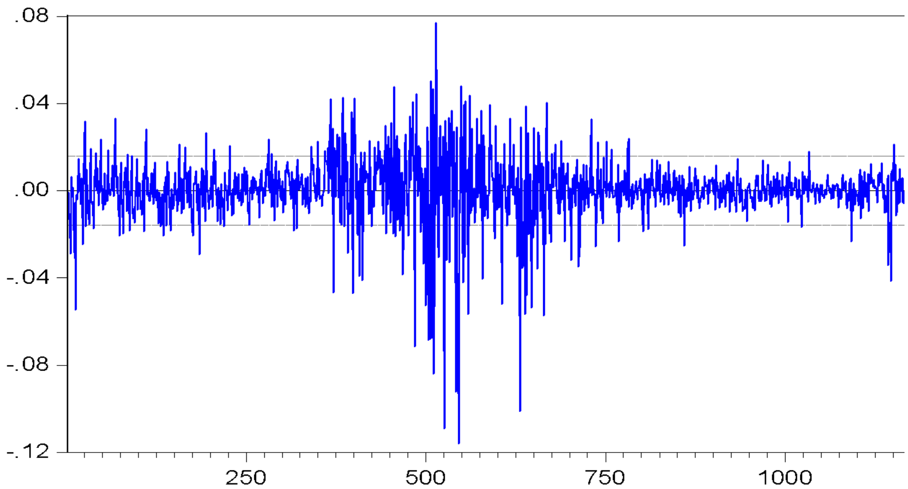

Figure 4 residual sequence line graph

It can be seen from the above test results that the residual sequence has a volatility aggregation phenomenon, indicating that the residual sequence may have heteroscedasticity. In order to further test whether the residual sequence has heteroscedasticity, the residual is subjected to ARCH test, the result is that the value of the F statistic is 73.10125, and the P value is 0.0000. As shown in Table 4, the rejection residual sequence has the assumption of the same variance, and the daily yield series is considered to have heteroscedasticity, which is suitable for establishing the volatility equation. In summary, the GARCH model to describe the volatility of the Shanghai Composite Index is reasonable.

Table 4 ARCH test

Heteroskedasticity Test: ARCH

F-statistic	73.10125	Prob. F(1,1233)	0.0000
Obs*R-squared	69.12178	Prob. Chi-Square(1)	0.0000

2.4 Model establishment:

Assuming that China's stock market is a weak effective market, that is, investors cannot use the current or historical price to predict the price of the stock. The logarithmic sequence of stock prices in this article is described by a random walk model in the form of: "LogP_t =$\beta Log\ P_{t-1} + \varepsilon_t$",among them, ε_t is a random error term.

Table 5 Random Walk Model Estimation Results

Dependent Variable: LOG(P)
Method: Least Squares
Date: 07/17/18 Time: 19:57
Sample (adjusted): 2 1237
Included observations: 1236 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(P(-1))	1.000019	5.62E-05	17779.78	0.0000
R-squared	0.994771	Mean dependent var		7.969269
Adjusted R-squared	0.994771	SD dependent var		0.217991
SE of regression	0.015764	Akaike info criterion		-5.461384
Sum squared resid	0.306897	Schwarz criterion		-5.457242
Log likelihood	3376.136	Hannan-Quinn criter.		-5.459826
Durbin-Watson stat	1.952469			

Use Eviews to build a random walk model to get the equation:

$$\mathrm{Log}P_t = 1.000019\mathrm{Log}P_{t-1},$$

From which you can find the coefficient of LogP_{t-1} is close to 1, so LogP_{t-1}obey the random walk process.

First of all,according to the previous ARCH test on the residual sequence, the GARCH(1,1) model is established for the residual sequence of the mean equation. As shown in Table 7, the model is:

$$\mathrm{Log}P_t = 1.000019\mathrm{Log}P_{t-1}+\varepsilon_t$$

$$\sigma_t^2 = 5.12 * 10^{-7} + 0.057499\varepsilon_{t-1}^2 + 0.941643\sigma_{t-1}^2$$

$$(1.37*10^{-7}) \quad (0.006182) \quad (0.004505)$$

The GARCH parameter reaches 0.941643, indicating that large fluctuations will be followed by large fluctuations. Small fluctuations will follow small fluctuations, reflecting the aggregation of volatility. AIC= -6.093402 in GARCH(1,1) model, the data is small, indicating that the GARCH(1,1) model has a good time series fit to the logarithmic price of the Shanghai Stock Index, so this article considers that it is appropriate to establish the GARCH(1,1) model.

Table 6 shows the results of GARCH(1,1) parameter estimation.

Dependent Variable: LP
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/17/18 Time: 20:02
Sample (adjusted): 2 1237
Included observations: 1236 after adjustments
Convergence achieved after 17 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000307	0.000264	1.162818	0.2449
	Variance Equation			
C	5.12E-07	1.37E-07	3.743612	0.0002
RESID(-1)^2	0.057499	0.006182	9.300570	0.0000
GARCH(-1)	0.941643	0.004505	209.0137	0.0000

III. Conclusion

In this article, the datas of the shanghai stock index from June 3, 2013 to June 29, 2018 as the sample of article. Through the statistical analysis of the daily yield, the results show that the daily return rate of China's stock market shows a significant fluctuation cluster. Second, the daily return rate of China's stock market has the characteristics of volatility clustering and asymmetry, while the return and risk are reversed,it means that there is no high risk accompanied by high return. Thirdly, a random walk model is established for the logarithmic price series of the Shanghai Stock Exchange Index. The GARCH model is built on the basis of this model. The results show that the model has a good fitting effect. It can be considered that GARCH is established for the daily yield series of the Shanghai Composite Index. GARCH(1,1) is a suitable for the model.

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