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Empirical Analysis of GARCH Effect of Shanghai Copper 1902 Futures

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Abstract: Micro financial data often has abrupt fluctuations in the stock market and futures markets. This is often referred to as a clustering phenomenon or a volatility cluster in financial time series. The GARCH model was originally used to analyze this volatile clustering phenomenon. This paper Based on the use of financial metrology analysis method to select 620 closing price data of Shanghai Copper 1902 Futures from November 26, 2015 to June 12, 2018, using GARCH model to estimate the yield and variance of each futures market in China's futures market. Of the yield, the EGARCH model is the best model for the fitting effect.

Keywords: Shanghai copper 1902 futures; yield; GARCH model.

1. GARCH (Autoregressive conditional heteroscedasticity) model introduction

ARCH was proposed by Prof. Robert Engle in 1982. Since its introduction, this model has been widely used in the econometric analysis of economics and finance. It is the fundamental model for analyzing the volatility of financial time series. The GARCH model is based on the ARCH model of Engle in 1986 by Bollerslev. It is called the “Generalized Autoregressive Conditional Heteroscedasticity” model. The TGARCH model and the EGARCH model are two typical asymmetric GARCH models.

2. Empirical analysis of the GARCH effect of Shanghai copper 1902 futures

2.1Sample data selection and processing

In order to better study the characteristics of the yield and volatility of the Chinese futures market, we chose the Shanghai Copper 1902 Futures Contract on the Shanghai Futures Exchange, which has a long history of trading, as its research object. Samples were taken from November 26, 2015 to 2018. On June 12th, a total of 620 data were selected from Great Wisdom 365 software.

2.2Stationarity Test (ADF Inspection)

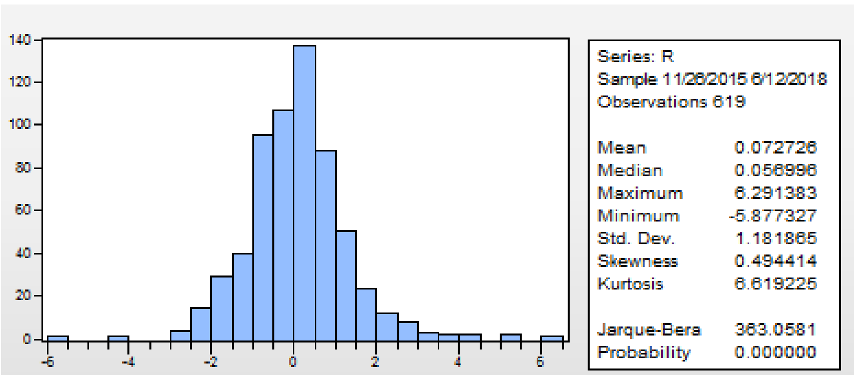

Figure 1

As can be seen from Figure 1, the futures yield shows a significant non-normal "spikes and thick tails" distribution characteristics. Before proceeding with the time series, we must first make sure the stationarity and use the ADF unit root test. The results are shown in Figure 2 below:

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.991388	0.7578
Test critical values:	1% level	-3.440685	
	5% level	-2.865991	
	10% level	-2.569199	

Figure 2

The sequence should accept the original hypothesis at the 1% level of significance, indicating that there is a unit root, the sequence of returns is non-stationary. The data used in the analysis of time series should have smoothness if Unsteady results in errors, so take the logarithmic rate of return to make it stable, the results are shown in Figure 3 below:

genr r=100*(log(p/p(-1)))

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.84022	0.0000
Test critical values:	1% level	-3.440702	
	5% level	-2.865999	
	10% level	-2.569203	

Figure 3

The sequence rejects the original hypothesis at a 1% level of significance, stating that no unit root exists, the rate of return sequence is stationary.

2.3 Select lag order

Date: 06/21/18 Time: 09:16
Sample: 11/26/2015 6/12/2018
Included observations: 619

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.033	-0.033	0.6627	0.416
		2	0.001	-0.000	0.6634	0.718
		3	-0.035	-0.035	1.4163	0.702
		4	0.021	0.019	1.6900	0.793
		5	-0.091	-0.090	6.8823	0.230
		6	0.008	0.001	6.9243	0.328
		7	0.064	0.066	9.4912	0.219
		8	0.009	0.007	9.5464	0.298
		9	0.017	0.022	9.7296	0.373
		10	0.059	0.057	11.905	0.291
		11	0.053	0.056	13.661	0.252
		12	-0.040	-0.025	14.695	0.259
		13	-0.016	-0.015	14.868	0.316
		14	-0.091	-0.094	20.171	0.125
		15	0.017	0.015	20.348	0.159

Figure 4

From Figure 4, we can see that the PACF is 5th-order truncated, so the AR model chooses p=2.

2.4OLS estimation

Ls r ar(5)

Dependent Variable: R
Method: Least Squares
Date: 06/21/18 Time: 08:43
Sample (adjusted): 12/04/2015 6/12/2018
Included observations: 614 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(5)	-0.087612	0.040223	-2.178150	0.0298

R-squared	0.003479	Mean dependent var	0.076832
Adjusted R-squared	0.003479	S.D. dependent var	1.181811
S.E. of regression	1.179754	Akaike info criterion	3.170116
Sum squared resid	853.1848	Schwarz criterion	3.177314
Log likelihood	-972.2255	Hannan-Quinn criter.	3.172915
Durbin-Watson stat	2.043626		

Figure 5

2.5 Heteroscedasticity test

The most commonly used LM test is used to test the ARCH effect. The test result is shown in Figure 6 below. At this time, the p-value is equal to 0, the original hypothesis is rejected, and the ARCH effect exists in the model. Therefore, the GARCH model can be established on the basis of the mean-value equation.

Heteroskedasticity Test: ARCH

F-statistic	49.13295	Prob. F(1,611)	0.0000
Obs*R-squared	45.62490	Prob. Chi-Square(1)	0.0000

Figure 6

2.6GARCH model

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/21/18 Time: 08:47
Sample (adjusted): 12/04/2015 6/12/2018
Included observations: 614 after adjustments
Convergence achieved after 10 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.
AR(5)	-0.083024	0.044529	-1.864465	0.0623
Variance Equation				
C	0.102042	0.034963	2.918609	0.0035
RESID(-1)^2	0.101627	0.020066	5.064771	0.0000
GARCH(-1)	0.819543	0.039780	20.60181	0.0000

R-squared	0.003458	Mean dependent var	0.076832
Adjusted R-squared	0.003458	S.D. dependent var	1.181811
S.E. of regression	1.179766	Akaike info criterion	3.042797
Sum squared resid	853.2029	Schwarz criterion	3.071592
Log likelihood	-930.1388	Hannan-Quinn criter.	3.053995
Durbin-Watson stat	2.043930		

Figure 7

As can be seen from Figure 7 above, since each p-value is less than 0.1, both the mean and variance equations hold.Its expression is:

$$y_t = -0.083024 y_{t-5} + \mu_t$$
$$\sigma_t^2 = 0.102042 + 0.101627 \mu_{t-1}^2 + 0.819543 \sigma_{t-1}^2$$

The ARCH test is used to test the residuals of the GARCH model using the most commonly used LM test. The test results are shown in the following figure. At this time, the p-value is greater than 0.05, and the original hypothesis is accepted, indicating that the ARCH effect does not exist in the model. Therefore, the established The model is suitable.

Heteroskedasticity Test: ARCH

F-statistic	0.032029	Prob. F(1,611)	0.8580
Obs*R-squared	0.032133	Prob. Chi-Square(1)	0.8577

Figure 8

2.7 TGARCH in Asymmetric Models

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/21/18 Time: 08:49
Sample (adjusted): 12/04/2015 6/12/2018
Included observations: 614 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(5)	-0.081481	0.043863	-1.857626	0.0632
Variance Equation				
C	0.105942	0.036821	2.877207	0.0040
RESID(-1)^2	0.115393	0.025157	4.586953	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.076872	0.028867	-2.662950	0.0077
GARCH(-1)	0.833191	0.043160	19.30486	0.0000

R-squared	0.003441	Mean dependent var	0.076832
Adjusted R-squared	0.003441	S.D. dependent var	1.181811
S.E. of regression	1.179776	Akaike info criterion	3.039789
Sum squared resid	853.2171	Schwarz criterion	3.075782
Log likelihood	-928.2152	Hannan-Quinn criter.	3.053786
Durbin-Watson stat	2.044032		

Figure 9

Both the mean and variance equations are also true.Its expression is:

$$y_t = -0.081481 y_{t-5} + \mu_t$$
$$\sigma_t^2 = 0.105942 + 0.115393 \mu_{t-1}^2 - 0.076872 \mu_{t-1}^2 I_{t-1} + 0.833191 \sigma_{t-1}^2$$

In the same way, heteroscedasticity tests are also performed on the residuals, and the ARCH test is performed on the residuals of the TGARCH model using the most commonly used LM test. The test results are shown in the following figure. At this time, the p-value is greater than 0.05, and the original hypothesis is accepted. It shows that there is no ARCH effect in the model, so the model is also suitable.

Heteroskedasticity Test: ARCH

F-statistic	0.000484	Prob. F(1,611)	0.9825
Obs*R-squared	0.000485	Prob. Chi-Square(1)	0.9824

Figure 10

2.8 EGARCH Model in Asymmetric Models

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/21/18 Time: 08:50
Sample (adjusted): 12/04/2015 6/12/2018
Included observations: 614 after adjustments
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(5)	-0.085698	0.045163	-1.897530	0.0578
Variance Equation				
C(2)	-0.136594	0.030371	-4.497559	0.0000
C(3)	0.190452	0.039918	4.771053	0.0000
C(4)	0.068952	0.018136	3.801974	0.0001
C(5)	0.929315	0.023109	40.21385	0.0000

R-squared	0.003475	Mean dependent var	0.076832
Adjusted R-squared	0.003475	S.D. dependent var	1.181811
S.E. of regression	1.179756	Akaike info criterion	3.036787
Sum squared resid	853.1879	Schwarz criterion	3.072781
Log likelihood	-927.2936	Hannan-Quinn criter.	3.050784
Durbin-Watson stat	2.043752		

Figure11

The mean and variance equations are established

Its expression is:

$$\gamma_t = -0.085698\gamma_{t-5} + \mu_t$$

$$\ln(\sigma_t^2) = -0.136594 + 0.190452\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}}} + 0.068952\frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}}} + 0.929315\ln\sigma_{t-1}^2$$

In the same way, we also need to test the heteroscedasticity of the residual error, and use the most commonly used LM test to perform ARCH test on the residuals of the EGARCH model. The test result is shown in the following figure. At this time, the p-value is greater than 0.05, accept the original hypothesis, It shows that there is no ARCH effect in the model, so the model is also suitable.

Heteroskedasticity Test: ARCH

F-statistic	0.055838	Prob. F(1,611)	0.8133
Obs*R-squared	0.056015	Prob. Chi-Square(1)	0.8129

Figure 12

2.9 The final choice of model

According to the above 2.6, 2.7, and 2.8 models, the AIC sizes are 3.042797, 3.039789, and 3.036787, and the SC sizes are 3.071592, 3.075782, and 3.072781. The EGARCH model is the best model for the fitting effect. Its expression is as follows:

$$\gamma_t = -0.085698\gamma_{t-5} + \mu_t$$

$$\ln(\sigma_t^2) = -0.136594 + 0.190452\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}}} + 0.068952\frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}}} + 0.929315\ln \sigma_{t-1}^2$$

3. Conclusion

Based on the daily closing price of Shanghai Copper 1902 Futures from November 26, 2015 to June 12, 2018, this paper uses three models: GARCH model, TGARCH model and EGARCH model for empirical analysis. According to the statistical characteristics of its return rate, a good model is fitted: EGARCH model, the conclusion is as follows:(1) The Shanghai copper 1902 futures yield has the following statistical characteristics (history = 6.619225) that have resulted in sharp fluctuations in the sequence, with significant ARCH effects, significant variability in aggregation, and EGARCH (1,5).) Has a good fitting effect.(2) EGARCH equation α1 + β1 is close to 1, indicating that the conditional variance function has unit root and single cohesive, that is, the conditional variance fluctuation has continuous memory, indicating that the persistence of the fluctuation of the return rate is stronger.(3) α1+β1<1 in the EGARCH equation indicates that the variance conditional variance sequence is stable and the model is predictable.(4) After the above analysis, the GARCHL model can predict the volatility of futures, estimate the yield and variance well, and the method is simple and easy to use. This proves that the GARCH model is widely used in the econometric analysis of economics and finance.

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