The Forecasting of China's Coal Futures Volatility Based on GARCH models

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Abstract

Steam coal is the core strategic resource of China's coal resources, which occupies the dominant status of coal. Under the background of steam coal supply-side reform, the price of steam coal futures has been rising, and its volatility has been widely concerned. Based on the daily price data of steam coal futures from September 2013 to the end of July 2018, the volatility of coal futures prices is studied by GARCH models. The empirical results show that the types of GARCH models can well fit the conditional heteroscedasticity of China's coal futures market, and the impact of the external impact on the volatility of coal futures returns is persistent and asymmetric; Steam coal futures market impact has a typical "leverage effect"; The estimated value and the actual value of the coal futures price estimated by TGARCH (1, 1) is more ideal, and the volatility of the coal futures yields sequence can be more effectively predicted under the t distribution.

Keywords

Steam coal futures,GARCH models, Volatility.

1. Introduction

In the financial and economic field, volatility is a key variable. Risk management and asset pricing are closely related to it. Therefore, the measurement of volatility and its dynamic characteristics are of great theoretical and practical significance. The volatility of futures price refers to the degree of deviation of futures price from its expected value. The greater the deviation, the greater the volatility of futures price. But in the financial research, we do not use the standard deviation of price to measure volatility, but the standard deviation of income to measure volatility. So in the empirical part, we use the daily return rate of coal futures price to judge the fluctuation of volatility. Because the volatility of financial market has the characteristics of explosion, persistence and aggregation, there are more and more forecasting methods for volatility, such as GARCH model, SV model and B-S model. For financial time series, GACRH family model is not only suitable for analyzing its conditional variance, but also can better fit the characteristics of its peak and thick tail. Therefore, we choose GARCH family model to estimate and forecast the volatility of China's coal futures.

2. Summary of Research

In the existing Volatility Prediction models, there are basically two kinds: one is historical volatility method, which is to use historical data to predict future volatility, such as GARCH family model and SV model in time series method; the other is implicit volatility method, which is to predict future volatility by inversion of Black-Scholes option pricing formula, such as B-S model. At present, the research on Volatility Prediction in China mainly focuses on time series model method. Taylor (1986) [1] proposed the SV model. Although it can fit the time series data well, because its volatility as an implicit variable is difficult to observe, it is extremely difficult to obtain an accurate likelihood function. Therefore, in the modeling of financial data fluctuation, scholars choose GARCH family model more.

After years of intensive research by many scholars, the ARCH model proposed by Engle (1982)[2] is considered as one of the effective methods to analyze the return and volatility, which better describes the volatility concentration caused by external shocks. ARCH model has made two breakthroughs in the development process. The first one is the GARCH model proposed by Bollerslev (1986) [3]. Although this model can better reflect the aggregation of volatility and reduce the impact of spikes and heavy tails in earnings series, it is difficult to explain its leverage effect. For this reason, scholars have proposed different asymmetric GARCH models, such as the index GARCH (E) proposed by Nelson (1991) [4]. GARCH model and Sentana (1991) [5] quadratic GARCH (QGARCH) model, Zakoian (1994) [6] threshold GARCH (TGARCH) model, etc. The second breakthrough in the development of ARCH model is due to long memory, which has been proved to be more effective in describing some long memory economic and financial phenomena, such as long memory ARCH model proposed by Ding [7], Bollerslev et al. (1996) [8]. The fractional monolithic FIGARCH model proposed by Keke and Zhang Shiying (2001) [9] contains the ARCH model in the literature better than the fractional monolithic augmented GARCH-M model proposed by Keke and Zhang Shiying (2001) [10].

The above research shows that GARCH family model can better measure financial data in volatility prediction. Xu Wei and Huang Yanlong (2008) [11] By comparing 11 models of risk Metrics and GARCH family to measure the accuracy of VaR value under normal distribution and Skewed-t distribution, they found that the VaR value predicted by GARCH family model under Skewed-t distribution was more accurate, and the risk degree of overestimation or underestimation was less. Zheng Zhenlong et al. (2010) [12] found that GARCH (1,1) had more information than implied volatility in short prediction period, and had the strongest ability to predict volatility. He Wan (2011) [13] Empirical study on volatility spillover effect between coal and oil prices using BEKK-MGARCH model shows that both of them have significant two-way asymmetric volatility spillover effect and positive correlation. Gu Peng and Zhang Jiebin (2015) [14] try to discuss whether there is price linkage effect between power coal futures market and coking coal futures market from two aspects: mean spillover effect and volatility spillover effect through VAR and BEKK-GARCH models. Liu Lin and Yang Wenjing (2016) [15] constructed MSVAR-Full BEKK-GARCH model to empirically study the mean spillover and volatility spillover effects among market sentiment, power coal futures price and spot price.

Coal futures is a product that can not be ignored. It is of great significance to analyze the fluctuation degree and characteristics of coal futures price for risk aversion and hedging in coal futures market. The purpose of this paper is to characterize the volatility of China's coal futures market by using GARCH models with different distributions. By comparing the accuracy of Volatility Measurement of different models under different distributions, we can find a better tool to describe the volatility of China's coal futures market, in order to help measure and forecast the risk of China's coal market and investors in investment decision-making.

The composition of this paper is as follows: The first part is the introduction, the second part gives a brief description of GARCH, EGARCH and TGARCH models, the third part is the selection of data and basic statistical analysis, and through the nuclear density formula to analyze the volatility distribution characteristics of coal futures prices, the fourth part is the empirical analysis and model comparison, and the last part is the summary of this paper.

3. Introduction of Two Families of Models

3.1 GARCH Model

GARCH model uses past variance and its predicted value to predict future variance of ARCH. Its advantage is that it can effectively eliminate excessive peaks in asset returns. The mathematical expression of GARCH (p, q) method is as follows:

$$\sigma_t^{\ 2} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon^2{}_{t-i} + \sum_{i=1}^{q} \beta_j \sigma^2{}_{t-j} \tag{1}$$

Among them, α_i and β_j are the estimated parameters, $\alpha_i \geq 0, \beta_j \geq 0$, q is the order of ARCH term P is the order of GARCH term.

3.2 2.2 EGARCH Model

EGARCH model is mainly used to measure the asymmetry of positive and negative interference on financial market volatility. The conditional variance equation of the model is as follows:

$$\ln \sigma_t^{\ 2} = \alpha_0 + \sum_{j=1}^{p} \beta_j \ln(\sigma^2{}_{t-j}) + \sum_{i=1}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}}} \tag{2}$$

EGARCH model adopts natural logarithm, which indicates that its leverage effect is exponential. In this model, parameter γ is introduced. when $\gamma \neq 0$,it shows that the information function is asymmetric. When $\gamma \prec 0$, which compared with positive shocks, financial markets are more volatile due to negative shocks, that is leverage effect.

3.3 2.3 TGARCH Model

In order to describe the rapid fluctuation more accurately, the TGARCH model sets a threshold to measure the impact of positive and negative shocks on conditional volatility by setting a fictitious variable.

$$\sigma_t^{\ 2} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k u_{t-k}^2 I^-{}_{t-K} \tag{3}$$

Among them, when $\varepsilon_t \geq 0$, $I_{t-k} = 0$; when $\varepsilon_t \leq 0$, $I_{t-k} = 1$.They mean that negative shocks cause greater fluctuations than positive shocks.

4. 3 Data and Statistical Description

4.1 3.1 Data Selection and Basic Statistical Analysis

The data are all from the windows database and collated. Because China's coal futures market is dominated by power coal futures, we choose the settlement price (active contract) date data of power coal futures as the coal futures price. From September 2013 to the end of July 2018, 1761 valid samples were obtained. For convenience, the coal futures price is recorded as F. Because of the discontinuity of the futures price of power coal, in order to solve this problem, a continuous futures price series is composed of data by linear method. Specific descriptions and statistics are as Table 1:

Table 1 Descriptive basic statistical analysis of coal futures price series

Sample	Max	Min	Mean	St.d	kurtosis	skewness	JB value	p value
F	695.200	282.200	506.49	99.983	2.214	-0.381	87.934	0.000

From Table 1, we can see that the skewness of power coal futures is less than 0, which indicates that the coal futures price series presents the left skewness distribution as a whole, and at 1% significance level, the series presents the characteristics of "peak and thick tail".

4.2 Basic Fluctuation Distribution Characteristics of Coal Futures Prices

Considering the volatility and relative amplitude of coal prices in recent years, this paper uses nuclear density estimation method to estimate the volatility distribution characteristics of coal futures prices. The standard nuclear density formula is as follows:

$$f_n(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \tag{4}$$

Among them, $K(\cdot)$ is a kernel function, n is the number of samples, h is the global smoothing parameter. Because the choice of the kernel function has little influence on the estimation results, we choose the Gauss nuclear density formula (2) to analyze:

$$k(x)=\varphi(x)=\frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}} \tag{5}$$

In this part, we choose EVIEWS software to characterize the kernel density estimation, where the number of bandwidth data points is set to 100. In this way, we can get the nuclear density estimation map of coal futures price, as shown in Fig. 1:

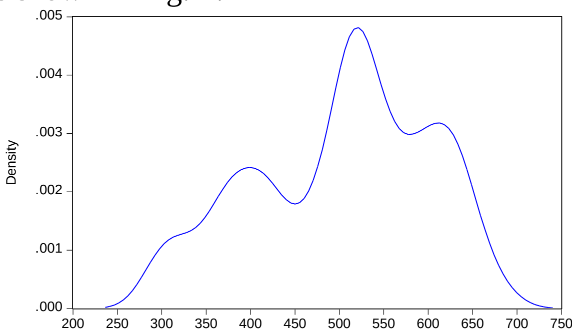

Fig. 1 Nuclear Density Map of Coal Futures

In the figure above, the abscissa represents the futures price of coal, and the ordinate represents the probability density of nuclear density. According to the figure above, we can clearly see the "double peak" pattern, and the gap between high price and low price is also very large, especially when the price is too high or too low, the nuclear density is too small, indicating that the probability of coal futures occurring when the price is too high or too low is very small; on the contrary, when the price is at a medium level, coal futures or spot occurs when the price is too high or too low. The probability is higher. At the same time, it can be seen that coal futures are "peak and heavy tail" distribution.

5. Empirical Analysis

5.1 Stationality and correlation test

Because GARCH model is suitable for analyzing stationary series and eliminating possible heteroscedasticity, it is necessary to process the sequence F to make it a relatively stationary profit sequence, namely LF:

$$LF_t=\log F_t-\log F_{t-1} \tag{6}$$

The ADF test is used to test the stationarity of the data. The test results are as Table 2:

Table 2 ADF test results

Sequence	t statistic	P value	1%	5%	10%	Test results
LF	-37.01169	0.00000	-3.433861	-2.862977	-2.567582	平稳

As can be seen from Table 2, $|t|>2$, and P value is 0, it is stationary in the test of coal futures return series, rejecting the unit root hypothesis at 1% significance level, so LF series is stationary. The correlation analysis of this sequence is shown in Table 3.

Table 3 Autocorrelation and partial correlation coefficients of LF sequences

Lag period	1	2	3	4	5
AC	0.1240	-0.0030	0.0230	-0.0280	0.0200
PAC	0.1240	-0.0180	0.0260	-0.0350	0.0290
Q- statistic	27.2850	27.2970	28.1960	29.6120	30.3280
P value	0.0000	0.0000	0.0000	0.0000	0.0000

By analyzing the correlation coefficients, we can see that the lagged first-order autocorrelation coefficient is larger than other orders. Therefore, a lagged first-order GARCH model is constructed by using LF sequence.

5.2 Least Square Method and Residual Test

The results of LF sequence fitting by least square method show that the LIKELIHOOD index is 7119.84400, the AIC and SC values are - 8.08387 and - 8.07765, respectively. We can see that the statistics are significant, the fitting degree is good, and there is a first-order truncation in the test process. Therefore, through the correlation test, we get the mean equation of the futures price return series LF as follows:

$$LF_t = 0.00003 + 0.12434 LF_{t-1} + \varepsilon_t \tag{7}$$

Although the statistics of Formula (7) are significant, the observation of residuals (Fig. 2) shows that the sequence LF has volatility clustering and time variability, which indicates that the error term of the sequence is likely to have conditional heteroscedasticity. Therefore, the ARCH LM test for equation (7) shows that the F statistic is 0.60001, the corresponding probability is 0.4386, the LM statistic is 0.6009, and the corresponding probability is 0.4382. The probability of the F statistic is less than the corresponding critical value and falls to the right of the corresponding critical value. Therefore, we reject the original hypothesis that there is ARCH effect and can establish GARCH model based on the AR (1) mean equation.

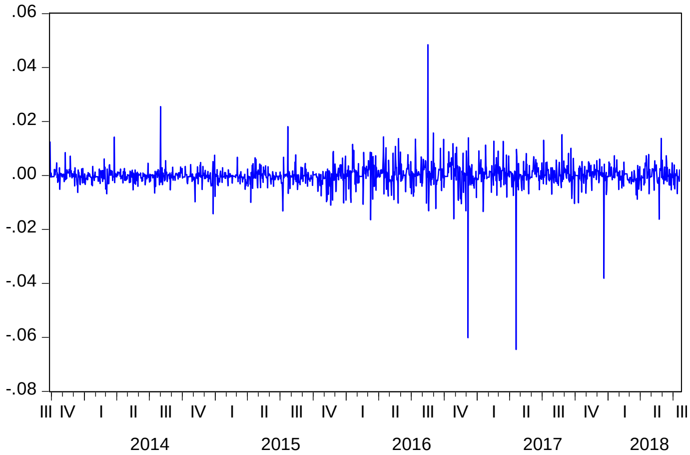

Fig. 2 Residual Diagram

5.3 GARCH Family Model Fitting Effect and Testing

In the existing volatility studies, financial time series usually have the characteristics of spikes and heavy tails. Therefore, we use GARCH, EGARCH and TGARCH models to estimate the conditional heteroscedasticity of coal futures yield under normal distribution, t distribution and GED distribution, respectively, and investigate the fitting effect of GARCH model. In the process of testing, we find that GARCH (1,2) has better fitting effect than other values of P and q. So we use GARCH (1,2) to test here. The remaining two models are EGARCH (1,1) and TGARCH (1,1), respectively. The results are shown in Table 4.

Table 4 Estimated results of volatility of coal futures

	GARCH z	GARCH t	GARCH GED	EGARCH z	EGARH t	EGARH GED	TGARCH z	TGARH t	TGARH GED
α_0	0.000	0.002	0.000	-11.838	-6.427	-8.890	0.000	0.002	0.000
	(29.763)	(0.061)	(13.306)	(-21.534)	(-3.354)	(-9.355)	(28.619)	(0.069)	(11.375)
α_1	0.388	557.451	1.145	0.426	2.937	0.742	0.090	523.795	0.873
	(27.062)	(0.061)	(5.815)	(18.108)	(0.741)	(11.633)	(6.713)	(0.069)	(3.491)
β_1	0.271	0.061	0.065	-0.057	0.308	0.252	0.721	0.033	0.028
	(10.649)	(2.678)	(2.897)	(-1.144)	(4.961)	(3.030)	(106.014)	(1.504)	(0.896)
β_2	0.359	-0.014	-0.018						
	(14.276)	(-2.622)	(-2.930)						
γ_1				-0.225	-0.109	-0.040	0.405	87.988	0.424
				(-10.123)	(-0.475)	(-0.736)	-15.914	-0.069	-1.127

AIC	-8.127	-8.976	-8.955	-8.143	-8.956	-8.953	-8.179	-8.978	-8.957
SC	-8.109	-8.954	-8.933	-8.125	-8.934	-8.931	-8.160	-8.956	-8.935
LL	7161.966	7910.028	7891.962	7176.319	7892.389	7890.144	7207.198	7912.246	7893.460

Comparing the AIC, SC and LL values of model estimation under normal distribution and t distribution, we find that the estimation effect under t distribution is better. Finally, comparing the AIC and BIC values of each model, we find that the effect of TGARCH (1,1) under t distribution is the best. Therefore, we establish the volatility equation of daily return series LF of coal futures as follows:

$$LF_t = -0.0000313 + 0.314919 LF_{t-1} + \varepsilon_t \tag{8}$$

(-0.075857) (15.23828)

$$\sigma_t^{\ 2} = 0.00189 + 523.7954\varepsilon^2{}_{(t-1)} + 87.98777\varepsilon^2{}_{(t-1)}(\varepsilon_{t-1} < 0) + 0.032502\sigma^2{}_{(t-1)} \tag{9}$$

(0.069589) (0.06959) (0.069163) (1.503743)

According to the above data, the ARCH coefficient is greater than 0, which indicates that external shocks will aggravate the volatility of coal futures market. The sum of ARCH coefficient and GARCH coefficient is obviously greater than 1, which indicates that the volatility of coal futures yield is more persistent. The coefficient of leverage effect is greater than 0, which indicates that the volatility of coal futures yield has leverage effect.

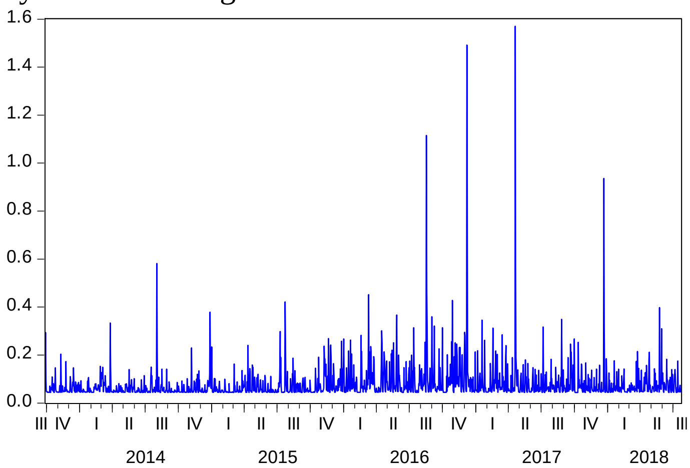

Fig.3 Time-varying volatility of coal futures yield

The time-varying volatility chart of daily return rate of coal futures fitted by TGARCH (1,1) model is shown in Fig. 3. We can see that the volatility of coal futures market in China has been relatively flat for a period of time after the establishment of coal futures market, basically at the level of 0.1. Since October 2015, the volatility began to intensify, and the volatility basically showed an upward trend. It is not difficult to see that the time-varying volatility is well simulated by the TGARCH model, and the volatility estimated by the TGARCH (1,1) model is consistent with the volatility of the return on assets. This shows that using time-varying volatility to estimate the price of coal futures is more in line with the actual situation than using fixed volatility.

The results of fitting output by TGARCH (1,1) model are shown in Fig. 4.

From Fig. 4, it can be seen that the actual value and estimated value of coal futures price fitted by TGARCH (1,1) are ideal. The probability of F and LM is 0.7764 and 0.7762 respectively. Therefore, there is no ARCH effect in the residual sequence. It shows that the conditional heteroscedasticity of the residual sequence of Formula (7) can be eliminated by using the TGACRH (1, l) model.

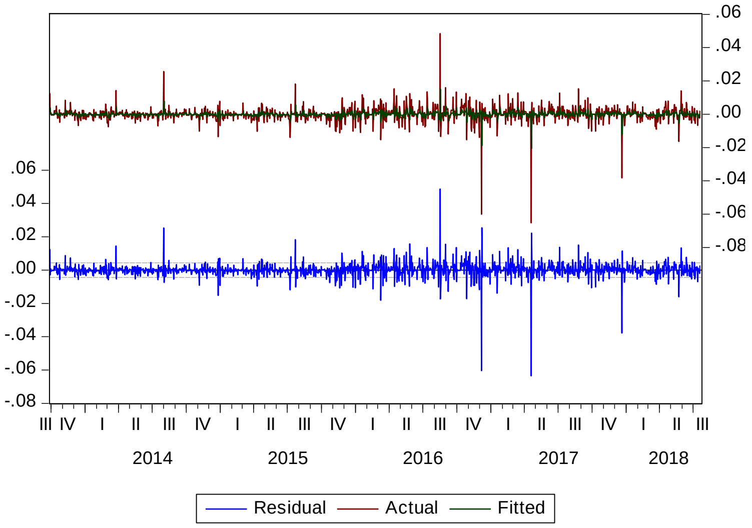

Fig. 4 Residual Value, Actual Value and Fitting Value of Coal Futures Return Sequence

5.4 Result Analysis

The GARCH (1,2), TGARCH and EGARCH models are used to measure the volatility of China's coal futures market under the sample of daily return series of coal futures prices. Empirical research shows that the overall fitting effect of the TGARCH (1,1) model under t distribution is the best. The concrete analysis results are as follows:

1) The daily return rate of coal futures price has significant heteroscedasticity. After filtering by GARCH (1,2), TGARCH and EGARCH models, the quantile value of the residual Ljun-Box Q statistic is no longer significant when it is less than 5% or 1%. This shows that the GARCH model is added to the mean equation in the coal price series, eliminating the autoregressive conditional heteroscedasticity in the residual series. According to the ARCH and GARCH coefficients in the futures equation fitted by TGARCH (1,1), we can see that the impact of external shocks on the volatility of coal futures returns is persistent and asymmetric.

2) Coal futures market shocks have typical "leverage effect". It shows that the fluctuation of coal futures market in our country has asymmetric information effect, which indicates that the fluctuation of coal futures price caused by a negative impact is stronger than that caused by a positive impact of the same degree.

3) Because of the particularity of coal futures, there is a deviation between the actual value and the estimated value. From the results, the actual value and estimated value of coal futures price fitted by TGARCH (1,1) are ideal. The actual value of coal futures price is overestimated by the market, and the actual value is higher than the estimated value. The main reason is the influence of stochastic volatility of coal futures price, which is consistent with the current policy of "capacity removal". Only when the market is relatively balanced, can we better use TGARCH (1,1) to predict the volatility of China's coal futures market.

4) Compared with normal distribution and GED distribution, t distribution can better describe the peak and thick tail characteristics of coal futures yield series. According to the AIC, SC and Log Likelihood values of the test results, the fitting effect of GARCH family model is poor under normal distribution and GED distribution, while the volatility equation fitted by each model under t distribution is better, and the phenomenon of overestimation or underestimation of coal futures yield by each model under t distribution is alleviated. The selection of models and probability distribution that can accurately reflect the fluctuation of coal futures price will provide a good solution for the managers of coal futures in China, and also play an important role in the selection of the best assets subject to probability distribution in the field of coal futures management.

6. Conclusion

Based on GARCH family model, the volatility of China's coal futures price is forecasted. Considering that the logarithmic series of coal futures price has the characteristics of "peak and heavy tail", and taking into account the random volatility of the series to adapt to the actual situation, it is found that the TGARCH (1,1) model can well fit the volatility of China's current coal futures market, and can achieve flexibility and flexibility in practical operation. The forecasting effect of the efficiency is of great significance to the selection of coal upstream and downstream enterprises and futures companies when they choose which probability distribution their assets are subject to. Under the background of coal market's capacity and inventory removal, coal enterprises need to manage their assets better through reasonable use of Volatility Prediction method, aiming at their own production and operation conditions, so as to improve their earnings and prevent the risk of excess inventory, so as to realize the sustainable development of enterprises.

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