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Research on risk mechanism of China's carbon financial market development from the perspective of ecological civilization

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A B S T R A C T

Based on examining the origin of Clean Development Mechanism (CDM) from a view of ecological conservation, this paper describes CER time series with GED distribution and discovers its heteroskedasticity. The TGARCH and EGARCH models both reflect significant volatility of CER price with GARCH model analysis. In our estimation of Chinese carbon market risk with econometric TGARCH-VaR and EGARCH-VaR models, we find that TGARCH-VaR and EGARCH-VaR models increase the accuracy in measuring the carbon market risk. To achieve the sound and increasing growth of China's carbon market, integration with the international market, and competition in the international carbon market, we argue the technical methods to reduce the market risk for the benefit of investors in the market competition. Our study provides more methods for China's carbon market risk measurement, so as to China's being well-prepared on the way to ecological economic development.

1. Introduction

Carbon market reveals both of its own risk features and other financial market risks as part of the financial market [1]. Carbon market risk consists of systematic risk and non-systematic risk [2]. Systematic risk is an extensive risk that exists in the carbon market impacted by politics and economics. The risk cannot be controlled whereas significant benefit can only be achieved with high risk. The non-systematic risk is caused by a single financial factor, which can be lowered through several methods even controlled. *Kyoto Protocol* proposes three international carbon trade mechanisms, wherein Clean Development Mechanism (CDM) primarily applies to the emerging market and the developed market [3]. Certified Emission Reduction (CER) issued in CDM is transacted in EU-ETS system in the European Union market [4]. Many factors have caused the volatility of CER price. First is the long development cycle of CDM program [5]. CER trade is characterized by forward contract where there is a long time between signing contract and final trade that causes a risk in exchange rate volatility [6]. Second, the impact of supply and demand, politics and economics on CER price has caused the significant volatility in the carbon market CER price, and thus the price risk to the investor [7]. Therefore, the investment in the carbon market faces greater risk than that in other markets [8]. This paper examines and measures the risk in CER carbon price in CDM program, and finds the proper risk estimation tool for prediction of CER price volatility, which can guarantee the benefit of the investor in market competition. This paper is useful to investigate CDM carbon market risk and to set up China's carbon market trade mechanism.

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The carbon financial market will generate carbon dioxide emission rights through the form of options, futures, and spot transactions, which will be subject to the carbon financial market mechanism [9]. Therefore, the more common financial market risk measurement methods in financial markets can also be applied to the carbon financial market, such as sensitivity analysis, scenario analysis, volatility methods and Value at Risk (VaR) method [10]. Among the wide variety of analytical methods, the Basel II and EU capital adequacy guidelines use VaR as the oversight standard, which is also the method used by central banks in most countries to measure risk [11]. Therefore, this paper also measures the risk of carbon financial market by VaR method. However, due to the particularity of its establishment, the carbon market is affected by the market mechanism as well as other markets. It is also affected by various complex environments, resulting in large fluctuations in carbon prices [12,13]. Therefore, when analyzing the risk of carbon financial market, it cannot be the same as other financial markets, only considering the usual assumptions, and fully considering the complexity of the carbon financial market futures price return sequence. Its income distribution often reflects the characteristics of spikes and thick tails. Based on this, this paper introduces the t-distribution and the Generalized Error Distribution (GED) for the characteristics of the peak and thick tail to describe the distribution characteristics of the carbon financial market price.

2. The distribution model, the GARCH family model and risk value model

2.1. T distribution model

The t distribution is closely related to the normal distribution and can be derived from a normal distribution and a χ^2 distribution [14]. The density function of the t distribution is:

$$f(x) = \frac{\Gamma[(n+1)/2]}{\sqrt{n\pi}\,\Gamma(n/2)}(1+\frac{x^2}{n})^{-(n+1)/2} \qquad -\infty < x < \infty \tag{1}$$

The t distribution is the same as the normal distribution and is symmetrical. The expected and variance of the random variable of the t distribution are 0 and $k/(k-2)$, respectively. It is obvious that the variance of the t distribution is larger than the variance of the standard normal distribution, and thus it can be seen that the t distribution embodies the characteristics of the thick tail. But as the degree of freedom n increases, the variance of the t-distribution will converge to 1, which will eventually approach a normal distribution. In the financial sector, the actual rate of return is often subject to the t-distribution, showing the characteristics of a sharp tail.

2.2. Generalized error distribution (GED) model

GED is a continuous probability distribution that is mainly used to deal with thick tail features [15]. Its density function is:

$$f(x) = \frac{\exp(-|x/\lambda|^{v})}{2\cdot\lambda\Gamma(\frac{1}{v})} \tag{2}$$

When v = 1, the distribution is reduced to a Laplacian distribution; when v = 2, and $\lambda = \sqrt{2}\sigma$, it becomes a normal distribution. When v<2, the density function image presents different peak and thick tail features. As the v value decreases, the peak and thick tail features become more and more obvious, that is, the probability of extreme events increases with the decrease of v. When v > 2, the density function image tail is thinner than the normal distribution tail. Therefore, the GED distribution is often used to describe in the financial domain time series.

2.3. GARCH family models

2.3.1. GARCH model

Poleslev (1986) proposed a generalized autoregressive conditional heteroskedasticity (GARCH) model [16]. The structure of the GARCH *(p,q)* model is as follows:

$$\begin{aligned} &y_t = X_t^T B + \varepsilon_t \\ &\varepsilon_t\,|\psi_{t-1} : N(0, h_t) \\ &h_t = \alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-1}^2 + \sum_{j=1}^{q}\beta_j h_{t-j} \end{aligned} \tag{3}$$

2.3.2. TGARCH model

As the information changes, the financial time series will be asymmetrical. In order to characterize the asymmetry of volatility, Zakoian (1994) proposed the TGARCH model to describe the fluctuation of the rate of return [17]. The mean model of this model is the same as the GARCH model, and the conditional variance is:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \varphi_k \varepsilon_{t-k}^2 d_{t-k} + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{4}$$

where, d_t is the nominal variable, $d_{t-k} = 1$, $\varepsilon_{t-k} < 0$; $d_{t-k} = 0$, $\varepsilon_{t-k} > 0$.

When the price rises, $\varphi \varepsilon_{t-k}^2 d_{t-k} = 0$, $\sum_{i=1}^{p} \alpha_i$ is used to refer to the influence of conditional heteroscedasticity; when the price reduces, $\sum_{i=1}^{p} \alpha_i + \sum_{k=1}^{r} \varphi_k$ is used to refer to its influence. If $\varphi_k = 0$, it means that the influence of price change information on price fluctuations is symmetrical; on the contrary, it is asymmetric, and there is leverage effect.

2.3.3. EGARCH model

Nelson (1991) proposed the exponential conditional heteroskedasticity (EGARCH) model [18], which does not impose any restrictions on the parameters, and the parameters well describe the asymmetry of the shock response to the shock. What is more, but the model can also effectively reduce the impact of individual observations on the overall model fit. Therefore, the EGARCH model is more common. Similarly, its mean model is the same as the previous ARCH family mean model, and the conditional variance is:

$$\ln h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{i=1}^{p} \varphi_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} + \sum_{j=1}^{q} \beta_j \ln h_{t-j} \tag{5}$$

Describe the conditional variance *ht* in the model in natural logarithm, indicating that *ht* has an exponential leverage effect and is non-negative. If $\varphi_i \neq 0$, the role of information is not symmetrical. When $\varphi_i < 0$, the leverage effect is significant.

2.4. Risk value model

2.4.1. Connotation of VaR

The meaning of VaR is: a certain maximum time interval and a given degree of confidence, due to market changes resulting in a maximum loss than the target level [19,20]. The definition of VaR is as follows:

$$P(X > VaR_p) = p \qquad VaR_p = F^{-1}(1-p) \tag{6}$$

where, X represents the profit or loss of holding an asset (or portfolio) within t time. At the confidence level p, VaR_p represents the VaR value. Its calculation formula is:

$$VaR_t = z_\alpha \cdot \sqrt{h_t} \tag{7}$$

where Z_α represents the quantile at a particular distribution, confidence level, and h_t represents the variance.

From the definition of VaR, VaR contains three key parameters: ①The holding period, which indicates the time when the risk manager holds the maximum loss of the assets. According the liquidity of the assets, the stronger the liquidity, the shorter the holding period is, and vice versa. ②Confidence level, the choice of confidence level depends on the degree of aversion of financial institutions to risk. Selecting a higher confidence level indicates that financial institutions have higher requirements for capital adequacy and are safer. Conversely, lower confidence levels are selected. ③Probability distribution (density) function of profit and loss. For the sake of simplicity, the probability density function of a normal distribution is usually taken as the standard. However, studies have shown that the returns of financial markets often reflect the characteristics of peaks and thick tails, so they are often described by t-distribution and generalized error distribution (GED) [21].

2.4.2. VaR calculation method

In general, the calculation of VaR has a more complicated measurement process. The key factors are mainly reflected in the probability distribution function of the return on assets or the estimation of the density function [22–24]. Based on this, a large number of calculation methods have been proposed by scholars. The main representative methods can be divided into three categories: parametric method, nonparametric method and semiparametric method.

① The parameter method, also called the variance–covariance analysis method, mainly focuses on the risk matrix method. It estimates the market risk of the portfolio based on historical volatility and correlation. The analysis of the portfolio value function method and the distribution of market factor obedience are the focus of the parametric approach. The initial calculation of the VaR parameter method mainly assumes that the yield is subject to a normal distribution, but this method is a static method with a large defect. For example, in the financial time series, clustering phenomenon often occurs, and there is an aggregation effect, which can also be called wave clustering. Therefore, in order to better portray this, to accurately calculate VaR, we must choose the appropriate probability distribution for the return on assets. This paper uses this method.

② Non-parametric methods are mainly based on historical simulation methods. Historical simulation is a relatively simple method, assuming that the future return of investment is consistent with the past. Simply calculate the average return of historical income, reorder from small to large, find the quantile at a certain confidence level, and finally calculate the VaR value.

③ The semi-parametric method is mainly based on extreme value theory and quantile regression. Through the analysis of VaR, it is found that the occurrence of extreme events has a greater impact on the determination of market risk. Therefore, the tail of the income distribution is modeled to improve the accurate measurement level of VaR. The extreme value theory is the spokesperson of this core idea.

2.4.3. VaR accuracy test

The VaR model is an important tool for measuring risk, and it is important to perform a fitness test on its model. At present, the methods for testing the accuracy and reliability of the VaR model mainly include pre-test and post-test methods. The pre-test method is specifically divided into stress test and scenario analysis. Post-testing is divided into return test, failure frequency test and interval prediction. Based on the extensive application of the failure frequency test method and the simplicity of the method, this paper uses this method to test the reliability and accuracy of the model.

The failure frequency test method [25] means that when the actual loss is higher than the VaR value, the fitting effect is considered to be poor, that is, failure; When the actual loss is lower than the VaR value, the fitting effect is considered to be good, that is, it is successful. Assume that the confidence of VaR is $1-\alpha$, the sample size is T, the number of days of failure is N, the frequency of failure is f = N/T, and the expected value of failure rate is α. According to the likelihood ratio LR proposed by Kupiec, the null hypothesis α = f is tested, that is, whether the failure rate of VaR is significantly equal to α:

$$LR = -2\ln[(1-\alpha)^{T-N}(\alpha)^{N}] + 2\ln[(1-f)^{T-N}(f)^{N}] \tag{8}$$

Under the condition of zero hypothesis, the χ^2 distribution with a LR degree of freedom of 1 has a 95% and 99% confidence interval threshold of 3.84 and 6.64, respectively. If LR>threshold, reject the null hypothesis, the VaR model estimates are not reliable.

3. Empirical analysis of GARCH-VaR model measuring carbon financial market risk

3.1. Sample selection and inspection

This paper selects the CER futures contract that the European Climate Exchange expires in December 2012 as the research object [26]. The sample interval is from March 18, 2008 to December 30, 2011, a total of 989 transaction data, using the futures contract settlement price as sample data. Use the natural logarithmic rate of return form to describe the daily trading rate, i.e., $R_t = 100 * (lnP_t - P_{t-1})$. The modeling and analysis tools in this paper use Eviews 6.0 software. Before using the VaR method for risk measurement, the normality, stationarity, autocorrelation, and conditional heteroskedasticity of the yield series should be tested.

3.1.1. Normality test

The VaR value can be determined according to different distributions. Therefore, this paper first analyzes whether the CER futures log yield timing obeys the normal distribution. On the basis of descriptive statistics, the time series graph and normal QQ graph are used to test the normality of the logarithmic rate of return distribution of CER futures, and the Eviews software is used to perform the statistical test of normality.

Using Eviews software to make a time series trend graph of CER futures logarithmic yield (Fig. 1), it is found that the logarithmic yield fluctuations are concentrated between (−10, 10). In the several periods with large fluctuations, the absolute value of the peak reaches a maximum of about 20, and then quickly falls back.

Using Eviews software to do the statistical characteristics of the logarithmic yield of CER futures R (Fig. 2), observe its skewness and kurtosis.

As can be seen from the above figure, the logarithm of the log yield of CER futures is −0.140494 (less than 0), which is left biased compared with the normal distribution, indicating that the left tail is closer to the right tail and the right side is the main body of the distribution. It can be inferred that the probability of generating a return is greater than the probability of occurrence of loss; the kurtosis value is higher than the peak of the normal distribution, which is 8.751029 (greater than 3), and can be judged as a spike characteristic. This means that the extreme events interfere with the carbon price, causing the yield to deviate from the normal value, and the characteristics of the thick tail appear; the Jarque–Bera value is 1347.818 (greater than 1% threshold 9.2103), with a probability of 0, rejecting the null hypothesis that the yield series obeys the normal distribution. At the same time, the QQ graph of the logarithmic yield series of CER futures (Fig. 3) can be visually found from the figure, and the distribution of the yield series does not obey the normal distribution.

Based on the above test and analysis results, it is shown that the CER futures logarithmic yield series does not obey the normal distribution feature and is an asymmetric "spike and thick tail" graph. Based on the above conclusions, the t-distribution and GED distribution are used to describe the actual data.

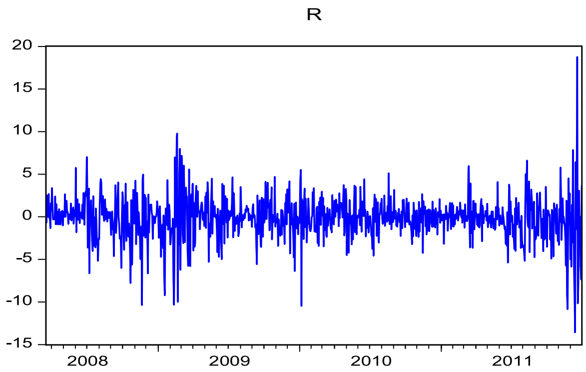


Fig. 1. CER futures DEC12 logarithmic yield time series diagram.

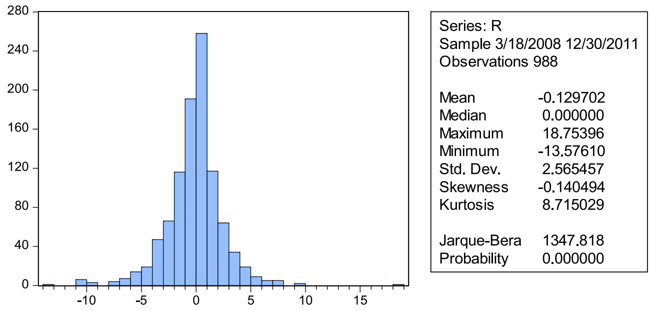


Fig. 2. CER futures DEC12 logarithmic yield statistical characteristics diagram.

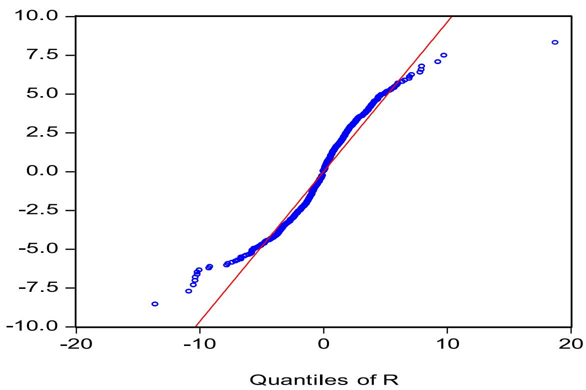


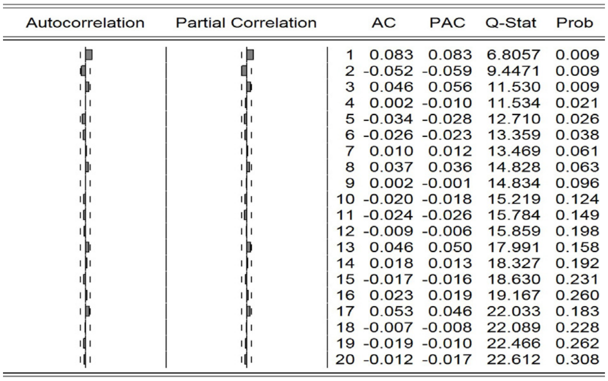
Fig. 3. CER futures DEC12 logarithmic yield QQ diagram.

3.1.2. Stationarity test

The ADF test is used to test the stationarity of the EUA futures logarithmic rate of return. The thresholds for confidence levels of 1%, 5%, and 10%, respectively, were −3.486756, −2.864257, −2.568269, and the ADF statistic was −28.84708, which was significantly less than the critical value at each confidence level. The test results show that under the 1% significance level, the CER futures logarithmic rate of return series rejects the null hypothesis and accepts the CER futures logarithmic rate of return sequence without the unit root.

3.1.3. Autocorrelation test

The Ljung–Box (1970) Q statistic is used to analyze the correlation of CER futures logarithmic yield series (see Fig. 4). It can be found that the accompanying probability P of the Q statistic is mostly greater than the significance level $\alpha = 0.05$, but is weakly correlated after the high order.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.083	0.083	6.8057	0.009
		2	-0.052	-0.059	9.4471	0.009
		3	0.046	0.056	11.530	0.009
		4	0.002	-0.010	11.534	0.021
		5	-0.034	-0.028	12.710	0.026
		6	-0.026	-0.023	13.359	0.038
		7	0.010	0.012	13.469	0.061
		8	0.037	0.036	14.828	0.063
		9	0.002	-0.001	14.834	0.096
		10	-0.020	-0.018	15.219	0.124
		11	-0.024	-0.026	15.784	0.149
		12	-0.009	-0.006	15.859	0.198
		13	0.046	0.050	17.991	0.158
		14	0.018	0.013	18.327	0.192
		15	-0.017	-0.016	18.630	0.231
		16	0.023	0.019	19.167	0.260
		17	0.053	0.046	22.033	0.183
		18	-0.007	-0.008	22.089	0.228
		19	-0.019	-0.010	22.466	0.262
		20	-0.012	-0.017	22.612	0.308

Fig. 4. R time series autocorrelation graph.

Table 1
CER futures logarithmic yield time series heteroscedasticity test results.

ARCH (q)	LM	Probability value	Conclusion
Q = 1	171.0617	0.0000	Heteroscedasticity
Q = 2	171.7973	0.0000	Heteroscedasticity
Q = 3	179.612	0.0000	Heteroscedasticity
Q = 4	224.8635	0.0000	Heteroscedasticity

3.1.4. Heteroscedasticity test

According to the analysis in Fig. 1, there is a cluster phenomenon in the logarithmic rate of return of CER futures, and it is judged that there may be heteroscedasticity. Therefore, the ARCH-LM test is performed in Table 1.

According to the heteroscedasticity test results in Table 1, it is shown that the yield series still has strong heteroscedasticity when the lag order is high. The heteroscedasticity test using the residual squared map is the same as the conclusion obtained in the above table. Therefore, it is reasonable to apply the GARCH family model to fit the logarithmic rate of return of CER futures.

3.2. Estimation of GARCH family models in carbon financial markets

According to the autocorrelation of carbon price and the tail condition of partial autocorrelation, according to the AIC criterion, this paper selects ARIMA (1,1) model modeling. According to the above test analysis results, the variance of the random error term of the CER futures yield series has high-order heteroscedasticity, so the GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models can be directly established. At the same time, the above analysis of CER logarithmic yield series has the characteristics of sharp peak tail, so we use the t distribution and GED distribution to fit the yield series. For comparison purposes, we also added the normal distribution to the GARCH family model. The parameter estimation results of the GARCH, EGARCH and TGARCH models based on different distributions are shown in Table 2.

The analysis of Table 2 is as follows:

Firstly, according to the *p*-value corresponding to the Z statistic in (.) of each parameter, the parameters in the conditional time-varying variance established by the above three models are significant at the confidence level of 5%. Through the ARCH-LM test of the estimated residuals of each model, it is found that there is no significant heteroscedasticity. It is reasonable to use the GARCH family model to fit the CER futures logarithmic yield series.

Secondly, according to the AIC criterion and the SC criterion, it is found that the student t distribution and the generalized error (GED) distribution are more suitable for fitting the CER futures logarithmic rate of return series than the normal distribution. Compared with the GED distribution, the GED distribution can better capture the distribution characteristics of the "peak and thick tail" of the CER futures logarithmic yield series. Therefore, the GARCH family model is further analyzed based on the GED distribution.

Thirdly, the analysis of the model GARCH(1,1) shows that the parameters α and β are both greater than 0, satisfying the model non-negative constraint; and $0 < \alpha 1 + \beta < 1$, satisfying the model is a stationary process, and the model is predictable. 11 reflects the degree of influence of external shock on the fluctuation of CER futures yield, and β reflects the memory of fluctuations in yield. When $\beta < 1$, the larger the β value, the slower the yield volatility reduction, and it will persist, that is, it has long-term memory. $11 + \beta = 0.972 < 1$, indicating that the volatility has a strong long-term persistence.

Fourthly, the analysis of the model EGARCH(1,1) shows that the estimated value of $\alpha 1$ is 0.35791, and the estimated value of the asymmetric term coefficient φ is -0.07448, which indicates that the negative shock can enhance the volatility

Table 2
CER futures logarithmic yield GARCH family model parameters estimates.

Distribution	Model	α_0	α_1	β	φ	AIC	SC	Log
Positive distribution	GARCH (1,1)	0.421461 (0.000)	0.224855 (0.000)	0.714081 (0.000)		4.3706	4.3855	−2156
	EGARCH (1,1)	−0.13173 (0.000)	0.37735 (0.000)	0.90310 (0.000)	−0.07431 (0.000)	4.3748	4.3946	−2157
	TGARCH (1,1)	0.424244 (0.000)	0.15335 (0.000)	0.71037 (0.000)	0.13904 (0.001)	4.3623	4.3822	−2151
t distribution	GARCH (1,1)	0.20362 (0.007)	0.21061 (0.000)	0.7862 (0.000)		4.3176	4.3374	−2128
	EGARCH (1,1)	−0.17915 (0.000)	0.34797 (0.000)	0.95279 (0.000)	−0.0743 (0.008)	4.3154	4.3402	−2126
	TGARCH (1,1)	0.2086 (0.004)	0.14087 (0.000)	0.78342 (0.000)	0.1328 (0.018)	4.3124	4.3372	−2125
GED distribution	GARCH (1,1)	0.275334 (0.002)	0.21428 (0.000)	0.75874 (0.000)		4.3103	4.3301	−2125
	EGARCH (1,1)	−0.16420 (0.000)	0.35791 (0.000)	0.93463 (0.000)	−0.07448 (0.016)	4.3110	4.3358	−2124
	TGARCH (1,1)	0.27984 (0.002)	0.14379 (0.000)	0.7567 (0.000)	0.1334 (0.030)	4.3056	4.3304	−2122

Note: The (.) in parentheses is the P values corresponding to the Z statistic.

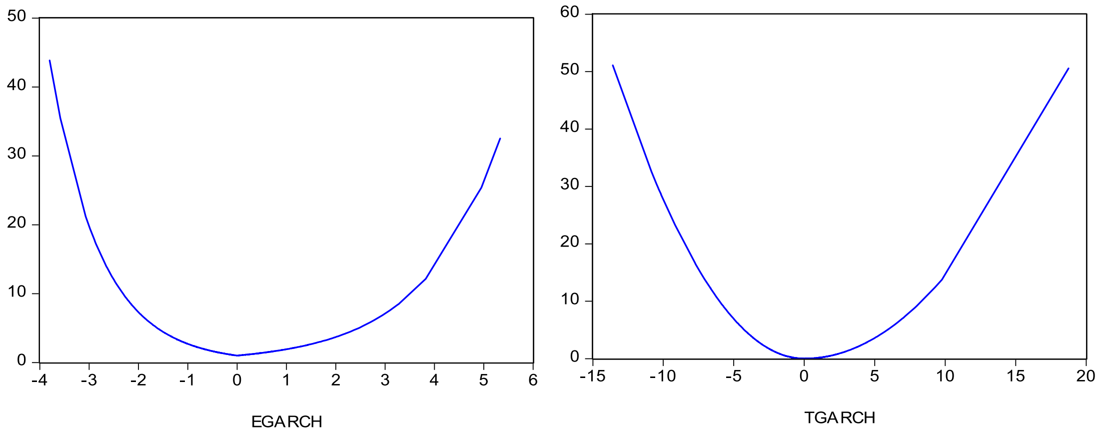


Fig. 5. EGARCH, TGARCH model information impact curve.

of CER futures yield. When εt-1 > 0, the "good news" has a 0.28343 times impact on the logarithm of the conditional variance; when εt-1 < 0, the "bad news" has a 0.43239 times impact on the conditional variance (see Figs. 7–5).

Fifthly, by analyzing the model TGARCH (1, 1), it is found that the leverage factor φ = 0.1334. This shows that the fluctuation of the logarithmic rate of return of CER futures has a "leverage effect": "bad news" will have a greater shock than "good news". When there is a "good news", εt-1 > 0, then dt-1 = 0, so the impact will only bring a 0.14379 times impact on the rate of return. When there is a "bad news", εt-1 < 0, at this time dt-1 = 1, this "bad news" will bring a 0.27719 times impact. In addition, the parameter p value in this model is not exactly equal to 0, but the model has the smallest AIC and SC, and the maximum log likelihood value is the largest (see Fig. 5).

In this paper, a comprehensive analysis of the above three models is carried out according to the AIC criterion, the minimum principle of the SC criterion, the maximum principle of the maximum log likelihood value, and the t-test result of the parameter estimation. It can be considered that the TGARCH (1, 1) model and the EGARCH (1, 1) model each have advantages. Therefore, the EGARCH(1,1) model and the TGARCH(1,1) model based on the GED distribution are selected to fit the CER futures logarithmic yield series, respectively, and finally determine the variance in the VaR value. The model is built as follows:

EGARCH (1,1) model:

$$\begin{aligned} &\mathrm{R} = \varepsilon_t \\ &\ln h_t = -0.16420 + 0.35791\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - 0.07448\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + 0.93463\ln h_{t-1} \end{aligned} \tag{9}$$

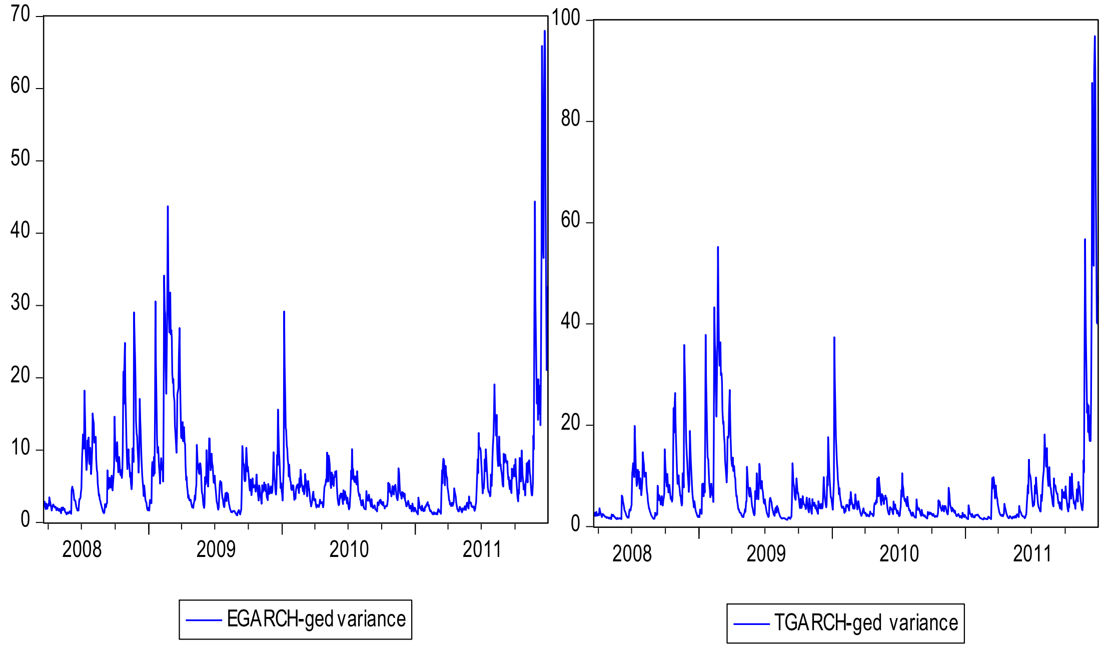


Fig. 6. EGARCH and TGARCH model carbon price heteroscedasticity diagram.

Table 3
GED distribution quantile.

Model	Parameter	Quantile	
		95%	99%
EGARCH	1.20744	1.64666	2.63977
TGARCH	1.22802	1.64765	2.62849

TGARCH (1,1) model:

$$\begin{aligned} R_t &= \varepsilon_t \\ h_t &= 0.27984 + 0.14379\varepsilon_{t-1}^2 + 0.1334\varepsilon_{t-1}^2 d_{t-1} + 0.7567h_{t-1} \end{aligned} \tag{10}$$

The trend of heteroscedasticity represents the level of fluctuations in carbon prices. As can be seen from Fig. 6, the carbon price fluctuations reflected by the EGARCH model and the TGARCH model are similar, reflecting the large fluctuations in carbon prices in the CER futures market, especially the CER futures market reflected by the TGARCH model. This large fluctuation indicates that there is an extreme risk in the carbon market, especially in the second half of 2011, the carbon market price continued to fall, and the emergence of extreme risks led to large fluctuations in the conditional heteroscedasticity [27]. It is thus proved that the conditional heteroscedasticity can better reflect extreme price fluctuations and extreme risks.

3.3. Analysis of VaR value in carbon financial market

According to the established GARCH family model, the EGARCH-VaR model and the TGARCH-VaR model were established to calculate the dynamic VaR of the carbon market. Firstly, quantiles at 95% and 99% confidence levels are determined based on the generalized error distribution (GED) parameters (see Table 3).

Secondly, calculate the VaR by the quantile and the estimated heteroscedasticity model (see Appendix A), and calculate the CER futures price risk in the ECX market under 95% and 99% confidence. The VaR value of the TGARCH model of DEC12 is shown in Figs. 7 and 8.

Thirdly, Test the prediction result of VaR by Kupiec's proportion of failures test. Calculate LR test and compare it with χ_α^2 (1). Calculate the result of GARACH-VaR model and select the best model. The time (T) is 988 days. Compare the predicted VaR and the actual VaR, and determine the failure days (N) and the proportion of failure (f). Determine the LR test value according to LR equation. Finally, determine whether the model can accurately fit the actual value (see Table 4).

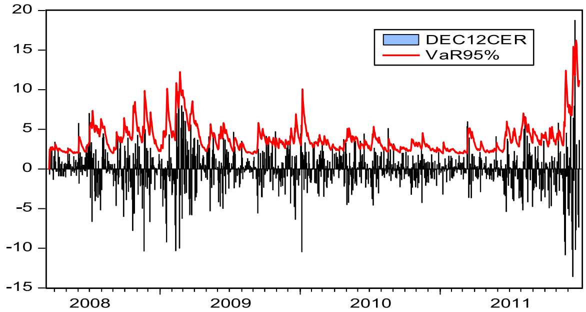


Fig. 7. 95% confidence level CER futures DEC12 yields and VaR value.

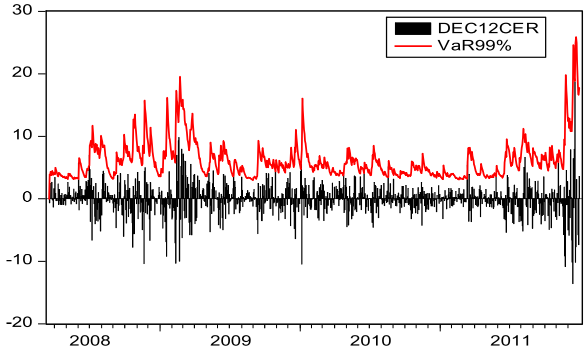


Fig. 8. 99% confidence level CER futures DEC12 yields and VaR value.

Table 4
GARCH-VaR results.

Model	Confidence level	Minimum VaR value	Maximum VaR value	Average VaR value	Standard VaR error	Days of failure	Expectation days	Failure rate	LR statistics
EGARCH(1,1)	95%	1.62878	13.5808	3.8425	1.724627	52	49.4	5.2632	0.1417
	99%	2.6111	21.7715	6.15994	2.76476	9	9.88	0.9109	0.081609
TGARCH(1,1)	95%	1.88997	16.2186	3.86798	1.977217	55	49.4	5.5668	0.6455
	99%	3.01506	25.8735	6.17058	3.154247	10	9.88	1.0121	0.001466

3.4. Model evaluation

First, TGARCH-VaR is valid to estimate the risk in the carbon market based on Generalized Error Distribution. The rate of return in diagram 7 and diagram 8 describes the circumstance when CER future return rate is greater than the estimated VaR. Wherein under the 95% confidence level, 55 points exceed VaR, and under 99% confidence level, 10 points. Under 95% confidence level, the LR test value is 0.6455, and under the 99% confidence level, 0.001466. The value is far less than the critical value 3.84(95%) and 6.64(99%), which displays good estimation by GARCH-VaR model on the risk of the samples. Table 4 reports that LR value estimated with EGARCH-VaR and TGARCH-VaR falls within the critical value range. The two models pass the test. Meanwhile, under the two confidence levels, the proportion of failure rates of the two models is respectively approximate to 5% and 1%, and LR value is smaller than the critical value. This verifies that the two models pass the test and estimate the market risk. Therefore, when the sample data is 988, 50 data exceeds the critical value range under 95% confidence level, and 10 data under 99% confidence level. The empirical result is acceptable.

Second, the failure frequency test method cannot be used to select the optimal model from the EGARCH model and the TGARCH model, because the two models are the same as the financial market asymmetric volatility model. At the 95% and 99% confidence levels, the minimum, maximum, mean, and standard deviation of the VaR calculated by the two models are generally similar, indicating that the two models are generally sensitive to fluctuations. It can be considered that the two models not only have better distribution fitting ability, but also can effectively portray the leverage effect. From the perspective of the fluctuation trend of CER futures yield, it can be concluded that there is a strong asymmetricity of information, so that the prediction accuracy is higher using both models.

4. Conclusion

China's carbon finance market is still in its infancy, but as the scale of market transactions expands, the increasing market risk will be an unavoidable reality for investors. To accurately measure the risk of carbon financial market will be an important topic for scholars to study in the future. This paper measures the market risk by establishing the GARCH-VaR model for the carbon financial market [28]. On the one hand, it is the theoretical basis for the construction of the risk mechanism of the carbon financial market. On the other hand, it provides an operational model for predicting the market risk of carbon financial market investors. Therefore, this paper uses the GARCH-VaR model to measure the risk of China's carbon financial market and has the following implications for the development of China's carbon financial market:

Firstly, in the risk valuation of carbon financial markets, China focuses on the distribution characteristics of the fluctuations in the yield of carbon financial markets. Through the research in this paper, it can be concluded that the carbon financial market has a distinct peak and thick tail characteristics compared with the general financial market. Therefore, the application of generalized error distribution (GED) can more accurately describe the distribution characteristics of carbon financial market price returns [29]. This paper studies the distribution characteristics of carbon financial market price returns, the purpose is to find out the characteristics of price behavior in carbon financial market, and price behavior is the core theory to explore the construction of risk mechanism in carbon financial market.

Secondly, in the risk valuation of carbon financial markets, China focuses on the heteroscedasticity of the price returns of carbon financial markets. According to the research in this paper, it can be concluded that the CER futures logarithmic rate of return series has strong heteroscedasticity after ARCH-LM test. Applying the GARCH family model to the CER futures logarithmic rate of return, we found that there is no significant heteroscedasticity. Therefore, it is reasonable for the GARCH family model to fit the CER futures log yield series. Because the study of the heteroscedasticity of the price returns of carbon finance market is to make the established risk measurement model more reflective of the real market risk situation. If there is heteroscedasticity in the model, it will interfere with the prediction results of the model, which may eventually lead to the destruction of the prediction function of the model.

Thirdly, in the risk valuation of carbon financial markets, China focuses on the predictability of models and the reflection of models on carbon financial market information. Through the research in this paper, it can be concluded that the fluctuation of the price of carbon market has long-term memory of carbon market information, and the fluctuation lasts for a long time. Therefore, in the development process of carbon financial market, policies and other information will act on the carbon financial market, which will have a violent and lasting impact on the carbon financial market.

Fourthly, in the risk valuation of carbon financial markets, China focuses on the impact of market information on the price of carbon financial markets. Through the research in this paper, we can find that by analyzing the models EGARCH(1,1) and TGARCH(1,1), it can be found that the impact of bad news on the price return rate of carbon financial market is stronger than the impact of good news on market yield. This shows that in the development process of carbon financial market, the impact of negative information on the development of carbon financial market in the market is far greater than the impact of positive information. If extreme risks or extreme events occur, it will be a fatal blow to the market and last for a long time. This theory has been confirmed in the development of the carbon financial market: the EU certification data leakage accident in May 2006, EU countries issued certification data in advance, so that investment funds flooded in, resulting in a rapid decline in carbon prices, carbon. The market has been in a downturn for a long time, and the price of carbon has fluctuated more than any period. The global financial crisis of 2008 had a serious impact on the price of carbon market, and the price fell from 20 euros to less than 10 euros, and lasted for several months.

Fifthly, China's focus on risk valuation of carbon financial markets is focused on the GARCH-VaR model's risk estimation for carbon markets. Through the research in this paper, it can be concluded that the carbon market risk value predicted by the GARCH-VaR model is compared with the actual value, and the risk estimate is within the critical value. This shows that the model can measure the carbon market risk more accurately, and the model is estimated to be effective. Compared with the current international VaR model for financial market risk valuation, the GARCH-VaR model improves the accuracy of China's carbon financial market risk valuation. Moreover, it can help China better develop the carbon financial market and provide theoretical support for China's carbon financial market risk measurement. This research work can reduce the investment risk of market participants, help China's carbon financial market to develop steadily, integrate with the international carbon finance market as soon as possible, and integrate into the international carbon financial market competition.

Finally, with the continuous growth of trading volume and trading sum in the carbon market, financial intermediaries and service providers actively engage in the carbon market. The market becomes more active, while the environment is more complex. Investors prefer to the short-term trading in the carbon market. Therefore, accurate measurement of the risk of the carbon market will bring significant economic benefits to all participants in the market. On the other hand, for local CDM program owners, the risk of price volatility in carbon market will affect the confidence of project owners and the effect of emission reduction. Therefore, investors expect minimized risk when trading in the market and obtaining benefit. To measure the risk of carbon market by TGARCH-VaR and EGARCH-VaR models can accurately reveal the risk and warn risks for investors. Our study can reduce the investment risk of market participants and help the setup of China's carbon market risk mechanism, so as to accelerate the integration of China's carbon market with the international carbon market, and engagement in the international carbon market competition. In addition, this paper provides more China's carbon market risk measurement methods, for China's being well-prepared on the way to ecological economic development.

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