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Estimating risk for the carbon market via extreme value theory: An empirical analysis of the EU ETS

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Abstract

With the rapid growth of the carbon market, carbon price fluctuations are increasingly important for market participants. Carbon market risk directly affects the investor confidence and emission reduction results. In the present study, extreme value theory (EVT) is used to analyze risk exposure for carbon price and to measure the Value at Risk (VaR) for the carbon market. GARCH models are applied to establish a model of price volatility for the spot market and the futures market and to calculate dynamic VaR. Traditional VaR and VaR based on EVT are also compared. The results show that the downside risk is higher than the upside risk for the carbon market. Upside and downside risks are higher in the first phase (Jun 2005–Dec 2007) than in the second phase (Feb 2008–Dec 2009) for both the spot and futures markets. Upside and downside risks are similar for the spot and futures markets during the same phase. The results also show that the EVT VaR is more effective than the traditional method, which can reduce the risks for market participants. Dynamic VaR based on GARCH and EVT can effectively measure the EU ETS market risk.

Keywords: EU ETS; VaR; GARCH; EVT; Carbon price; Risk measurement

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1 Introduction

Greenhouse gas emission credits are now a scarce resource, so the international greenhouse gas emission trading market (carbon market) has developed rapidly. The European Union Emissions Trading Scheme (EU ETS) is the largest carbon market. The EU ETS trading volume increased from 322 million tons in 2005 to 6326 million tons in 2009, and the trading value increased from US$8.2 billion in 2005 to US$1184.74 billion in 2009 [1, 2].

EU ETS has opened new business opportunities for financial capital. The value with the rapid growth in EU ETS trading volumes, an increasing number of financial intermediaries and service providers are participating in the scheme, the carbon market is from general trading markets, as international politics and negotiations leads to great volatility, so that the market situation is becoming increasingly complex. Speculators are more concerned about short-term operation than long-term price trends, as evidenced by the rapid growth in turnover of futures contracts. Effective measurement of EU ETS market risk is of practical importance for market participants. EU ETS carbon price fluctuations will affect the confidence of market participants because of the uncertain politics and negotiations and thus the demand for emission reduction quotas.

Carbon futures and options are traded in the EU ETS and have the properties of goods. The market mechanism has a great influence on carbon prices, carbon price will raise when the carbon allocation demand is strong, otherwise carbon price maybe down. Therefore, general measurement methods for financial market risk such as the Value at Risk (VaR) also apply to the carbon market. However, as a special commodity, carbon has its own traits that are differ from financial products. As a new market, the carbon market is impacted by external environmental instability (special event such as political factors and international climate negotiations, National Allocation Plan, temperature, among others) [3, 4]. The special events in the EU ETS may lead to an unusual loss or gain, For instance, in May 2006, the Czech Republic, France and Sweden made announcements showing their positions would be longer than expected. With the influx of speculative funds, the carbon price fell quickly, which made the market weak and.

Description of the distribution of special events and modeling the risk of such events are important issues in market risk measurement. The main problem is modeling the distribution tail for the returns. For the EU ETS, the distribution tail may reflect special events that could cause great losses to EU ETS participants, which should be a major consideration in EU ETS risk management. Therefore, assuming that carbon price returns follow a certain type of distribution (commonly a normal distribution) can lead to biased results. In fact, because of the complexity of carbon price returns series, the middle of the returns distribution is inconsistent with the tail, which is unique. Thus, extreme value theory (EVT), which can measure extreme tail risk, was used to assess the carbon market risk.

The carbon market risk has quite distinct implications for disparate market participants. For example, when carbon prices slump, carbon sellers incur losses. In this scenario, profits increase among purchasers; when the carbon price increases, the outcome is reversed. Therefore, in contrast to risk measurement in financial markets, both the downside and upside risks have to be considered in the carbon market.

The remainder of the paper is organized as follows. Section 2 reviews the VaR measurement methods applied. Section 3 describes the source data. Empirical results are presented and discussed for static VaR, the GARCH model and dynamic VaR in Section 4. Conclusions are offered in Section 5.

2 Literatures of EU ETS and carbon market risks

With the greater focus on climate change actions and the rapid development of EU ETS impacts, great attention is being paid to carbon emissions [5-7] and the emerging carbon market [8]. To date, research on carbon market mechanisms and prices has focused on several areas, including the relationship between carbon, energy and stock prices. Benz and Trück [9] studied differences between emission allowances and classical stocks. Whereas the demand for and value of a stock is based on profit expectations for the underlying firm, the CO_2 allowance price is determined by the expected market scarcity induced by current demand and supply in the carbon market. Mansanet-Bataller et al. [10] used econometric tools to analyze the relationship between carbon prices and oil, gas, coal and extreme weather phenomena. Alberola et al. [11] established a model including carbon price, energy prices and weather to analyze carbon price changes and the impact of EU ETS structural break points from 2005 to 2007. Oberndorfer [12] researched the impact of stock prices for power companies on EU ETS carbon prices. The results showed that carbon prices were positively correlated with stock prices, although this effect was not asymmetric. Benz and Trück [13] established Markov switching and AR-GARCH models to study returns on emission allowances. Wei et al. [14, 15] studied the relationships between carbon prices and energy prices. Feng et al. [16] examined carbon price volatility from a nonlinear dynamics point of view.

Research has also focused on relationships between the industrial economy and other macro factors and the EU ETS. Lund [17] investigated the impact of EU ETS costs on energy-intensive manufacturing industries. Abadie and Chamorro [18] assessed installation of a carbon capture and storage (CCS) unit in a coal-fired power plant operating in a carbon-constrained environment in terms of the carbon price risk and the price of electricity output. Chevallier [19] used a GARCH model to explain the relationship between EU ETS carbon futures and macroeconomic factors. Analysis showed that the EU emissions allowances (EUAs), as a new type of commodity, were obviously influenced by electricity demand. Alberola et al. [20] confirmed the impact of variations in industrial production on EUA price changes in four countries (Germany, Spain Poland and the UK) and underlined the central role played by German power producers in the EU ETS.

Other factors affect the price of carbon, including weather conditions (temperature, rainfall, wind speed), which affect power-generating capacity and the demand for emissions allowances, energy prices and macroeconomic trends. Benz and Trück [9] showed that an energy structural change would affect the supply of emissions allowances; the carbon emissions demand of power plant using natural gas was at least 50% less than that of a coal-fired plant. Feng et al. [21] verified carbon market is temperature-sensitive.

The allocation of EUAs has also been investigated. Buchner et al. [22] summarized the lessons and general principles to be learned from the allocation of allowances in the EU ETS, as well as global implications of the EU ETS. Haar and Haar [23] researched EU ETS policy-making uncertainties from a qualitative point of view, including the potential impact on economic development, the role of reductions in greenhouse gas emissions, and the benefits and costs of such reductions. They found that officially sponsored research and academic efforts in support of the EU ETS are surprisingly limited. Chevallier et al. [3] evaluated the impact of the 2006 compliance event on change in investor risk aversion in the European carbon market. The results show evidence of a dramatic change in the market perception of risk around the event. Parsons [24] compared the impact of banking and borrowing on carbon price fluctuations by comparing CO_2 price fluctuations in the US and the EU ETS. Alberola and Chevallier [4] provided evidence that banking restrictions contributed to low EUA phase I prices. EUA spot prices did not meet equilibrium conditions in the intertemporal permits market. Other research focus on EUA price effecting on the value of corporations, Busch and Hoffmann [25] studied the financial markets perceive carbon constraints.

Research on risk analysis in EU ETS is few, Chevallier [26] studied the risk premia in CO2 allowances spot and futures prices. Chevallier [27] investigated the carbon price risk in the UK power sector. There has been no direct risk analysis for the EU ETS market, although EU ETS price fluctuations have been discussed. The aim of the present study was to explore risks for the EU ETS market via EVT.

EVT has been applied in many fields where extreme values occur. Such fields range from finance [28, 29] to insurance [30] and the oil market [31]. EVT provides a solid framework to formally study the behavior of extreme observations. However, price returns often show a clustering phenomenon and heteroscedasticity, so the GARCH model is used here to describe returns. A VaR model with GARCH is an accurate way to describe this phenomenon [32]. Marimoutou et al. [31] established a VaR model with EVT to study the oil market. Kuester et al. [33] compared the out-of-sample performance of existing methods and some new models for predicting Value-at-Risk. The results showed a heavy-tailed GARCH filter with an EVT-based approach, performed best overall. In the paper we model VaR using GRACH and EVT to identify the best measurement of carbon market risk.

3 Methodology

Let C_t denote the carbon price, so carbon price returns r_t are:

$$r_t = 100 \times (\ln C_t - \ln C_{t-1}) \,. \tag{1}$$

3.1 VaR

VaR is one of the most popular approaches for measuring market risk. VaR is defined as the maximum loss that will be incurred on a portfolio at a given confidence level over a specified period. Let $F(x)$ be the distribution function for carbon price returns and p be the VaR confidence level. Then VaR can be represented as:

$$P(X > VaR_p) = p, \quad VaR_p = F^{-1}(1-p) \,. \tag{2}$$

The expected shortfall (ES) is used to assess conditional expected losses that exceed VaR [34, 35]. ES measures the average loss value when the loss exceeds VaR. If we define VaR as q, ES can be expressed as:

$$E[X \mid X < q] = \frac{\int_{-\infty}^{q} xf(x)dx}{\int_{-\infty}^{q} f(x)dx}. \tag{3}$$

3.2 GARCH

The clustering phenomenon and heteroscedasticity of carbon price returns volatility are obvious in the EU ETS; these can be described by the standard ARCH model and GARCH model [36, 37].

The GARCH model for the EU ETS can be expressed as follows:

$$\begin{aligned} y_t &= \mathbf{x}_t^{'}\beta + \varepsilon_t \\ h_t &= \alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j h_{t-j} \\ \varepsilon_t &= \nu_t\sqrt{h_t} \end{aligned}, \tag{4}$$

where $x_t^{'} = (r_1, \cdots r_t)^{'}$ denotes carbon price returns, h_t is conditional variance and ν_t is a random variable that is independent and identically distributed and independent of h_t.

The current volatility of returns caused by previous increases and decreases in carbon price returns are quite asymmetric, which is called the leverage effect. TGARCH models are applied to address these issues[1]. The residual distribution is selected according to AIC, this will include a normal distribution and a generalized error distribution (GED) [40].

3.3 Extreme Value Theory

EVT was developed from Gumbel, Fréchet and Weibull distributions to yield a generalized extreme value distribution (GEV) as suggested by Jenkinson [41]. A more efficient approach to modeling extreme events is to attempt to focus not only the largest (maximum) events, but on all events greater than some large preset threshold. This is referred to as peaks over threshold (POT) modeling [31, 42].

We define the excess distribution above the threshold u as the carbon price returns conditional probability $F_u(y)$:

$$F_u(y) = \mathrm{P}(r' - u \le y \mid r' > u) = \frac{F(u+y) - F(u)}{1 - F(u)} \quad (y > 0), \tag{5}$$

[1] See Glosten et al.[38] and Zakoian [39] for an extensive discussion on this topic.

where r_t' is the residual of the GARCH model. For a sufficiently high threshold u, the distribution function of the excess may be approximated by the generalized Pareto distribution (GPD) [43, 44]. The excess distribution $F_u(y)$ converges to the GPD:

$$F_u(y) \approx G'_{\xi,\beta}(y) = \begin{cases} 1-(1+\dfrac{\xi}{\beta}y)^{-1/\xi} & if \ \ \xi \neq 0 \\ 1-e^{-y/\beta} & if \ \ \xi = 0 \end{cases} \qquad u \to \infty\,, \tag{6}$$

where $y \in [0,\infty)$ for $\xi \geq 0$ and $y \in [0,-\beta/\xi]$ for $\xi < 0$. $G'_{\xi,\beta}(y)$ is the GPD. ξ and β are the shape parameter and scale parameter for carbon price returns, respectively. ξ is an important parameter because it reflects the rate of disappearance of the distribution tail.

According to Eq.(7), for a given carbon price return residual $\{r_1',\cdots,r_n'\}$ that meets the GPD, the maximum likelihood function is:

$$L(\xi,\beta \mid y) = \begin{cases} -n\ln\beta-(1+\dfrac{1}{\xi})\displaystyle\sum_{i=1}^{n}\ln(1+\dfrac{\xi}{\beta}y_i) & \xi \neq 0 \\ -n\ln\beta-\dfrac{1}{\beta}\displaystyle\sum_{i=1}^{n}y_i & \xi = 0 \end{cases} \tag{7}$$

For a given threshold u, n is the sample size for carbon price residuals and N_u is the number of samples that exceed u. $F(r')$ are represented by:

$$F(r') = F_u(y)(1-F(u))+F(u) \tag{8}$$

and the function $F(u)$ can be estimated non-parametrically using the empirical cumulative distribution function:

$$\hat{F}(u) = \frac{n-N_u}{n}\,. \tag{9}$$

After substituting Eqs. (7) and (10) into Eq.(9), we obtain the following estimate for $F(r_t')$:

$$\begin{aligned} F(r_t') &= (\frac{N_u}{n})[1-(1+\frac{\xi}{\beta}(r_t'-u))^{-1/\xi}]+(1-\frac{N_u}{n}) \\ &= 1-\frac{N_u}{n}[1+\frac{\xi}{\beta}(r_t'-u)]^{-1/\xi} \end{aligned}\,. \tag{10}$$

For $p > F(u)$, VaR_p can be obtained as:

$$VaR_p = u + \frac{\beta}{\xi}\left[\frac{n}{N_u}(1-p)^{-\xi} - 1\right]. \tag{11}$$

ES is expressed as:

$$ES_p = \frac{VaR_p}{1-\xi} + \frac{\beta - \xi u}{1-\xi}. \tag{12}$$

3.4 Static VaR, dynamic VaR calculation and back testing

On the basis of the VaR definition above, we can use Eqs.(12) and (13) to calculate the static VaR and ES. The dynamic VaR for the upside VaR can be calculated as follows:

$$VaR_{m,t}^{up} = \mu_{m,t} - z_{m,\alpha}\sqrt{h_{m,t}} \quad (m = 1, 2), \tag{13}$$

where $\mu_{m,t}$ is the conditional expected return for carbon market m and $z_{m,\alpha}$ denotes the left α-quantile, which is the VaR_p in Eq. (12). $h_{m,t}$ is the conditional variance series in market m, so $h_{m,t}$ >0. The downside VaR can be calculated as follows:

$$VaR_{m,t}^{down} = -\mu_{m,t} + z_{m,\alpha}\sqrt{h_{m,t}} \quad (m = 1, 2). \tag{14}$$

After calculating the VaRs, for reliability it is necessary to back test whether the VaR model used has adequately estimated the real extreme risk or not. The failure rate is widely applied in studying the effectiveness of VaR models. The definition of failure rate is the proportion of the number of times the observations exceed the forecasted VaR to the number of all observations. The standard we use to judge the performance of VaR model is to assess the difference between the pre-specified VaR level and the failure rate. If the failure rate is very close to the pre-specified VaR level, we could conclude that the VaR model is specified very well [45]. According to Kupiec [46], we assume a confidence level $1-\alpha$, sample size T and time to failure N days; then the failure rate is $f=N/T$. Kupiec [46] proposed the most suitable likelihood ratio test with the null hypothesis $\alpha=f$, for which the statistic is:

$$LR = -2\ln\left[(1-\alpha)^{T-N}(\alpha)^{N}\right] + 2\ln\left[(1-f)^{T-N}(f)^{N}\right] \quad . \tag{15}$$

Under the null hypothesis, $LR \sim \chi^2(1)$ and the critical values at 95% and 99% confidence levels are 3.84 and 6.64, respectively. According to the definition of a χ^2 distribution, if LR is greater than the corresponding critical value, then the null hypothesis should be rejected; in other words, it can be said that the VaR model is not adequate.

4 Data

The EU ETS, in its first phase from January 1 2005 to December 31 2007, regulates CO2 emissions from installations representing some 40% of EU emissions. The second phase is from 2008 according to Directive 2003/87/EC. The Bluenext carbon spot market and the European Climate Exchange (ECX) carbon futures market are analyzed here.[2] Several major carbon price series are selected for the study: spot prices in the first phase (Spot1), futures for delivery in December 2007 (DEC07), spot prices in the second phase (Spot2), and futures for delivery in December 2009 (DEC09).

First-phase data are from June 2005 to December 2007 and second-phase data are from February 2008 to December 2009, and are quoted in EUR per ton. However, some prices are missing between spot and futures prices. We interpolate missing prices using average values. The carbon price trend is shown in Fig. 1.

Because the data include four price series, Spot1 is used as the sample in the modeling EVT process. The main example focuses on DEC09 in calculating the dynamic VaR.

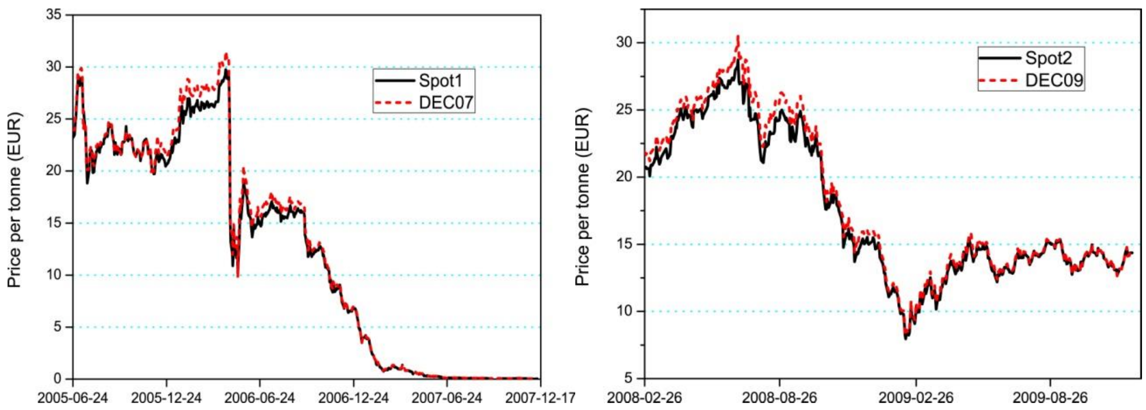

Fig. 1. Daily spot and futures prices for the first and second phases.

[2] The first phase of the spot market was named Powernext. The NYSE acquired the Powernext environmental business on December 21, 2007, including Powernext Carbon and Powernext Weather, and renamed the new market Bluenext.

Data source: Bluenext; ECX.

5 Results Analysis and discussions

5.1 Summary statistics for carbon price returns

According to Eq.(1), carbon price returns were obtained and their trends are evident in Fig. 2. It should be noted that both spot prices (Fig. 2a,c) and futures prices (Fig. 2b,d) reveal the phenomenon of volatility clustering. The basic statistical characteristics of spot and futures price returns during the sample period are shown in Table 1. Overall, first phase fluctuations are large, and returns and volatility levels for spot and futures prices in the second phase are similar (the vertical range in Fig. 2a,c is much greater than that in Fig. 2b,d). Compared with the standard normal distribution with skewness 0 and kurtosis 3, the skewness of both returns is negative, especially for DEC07. In other words, the returns do not follow the standard normal distribution. This was verified using the Jarque Bera (JB) test. A Ljung Box (LB) test confirmed that spot and futures returns both exhibit significant autocorrelation. In addition, both returns are stationary series according to an ADF unit root test. GARCH modeling for spot and futures returns is described in Section 4.3.

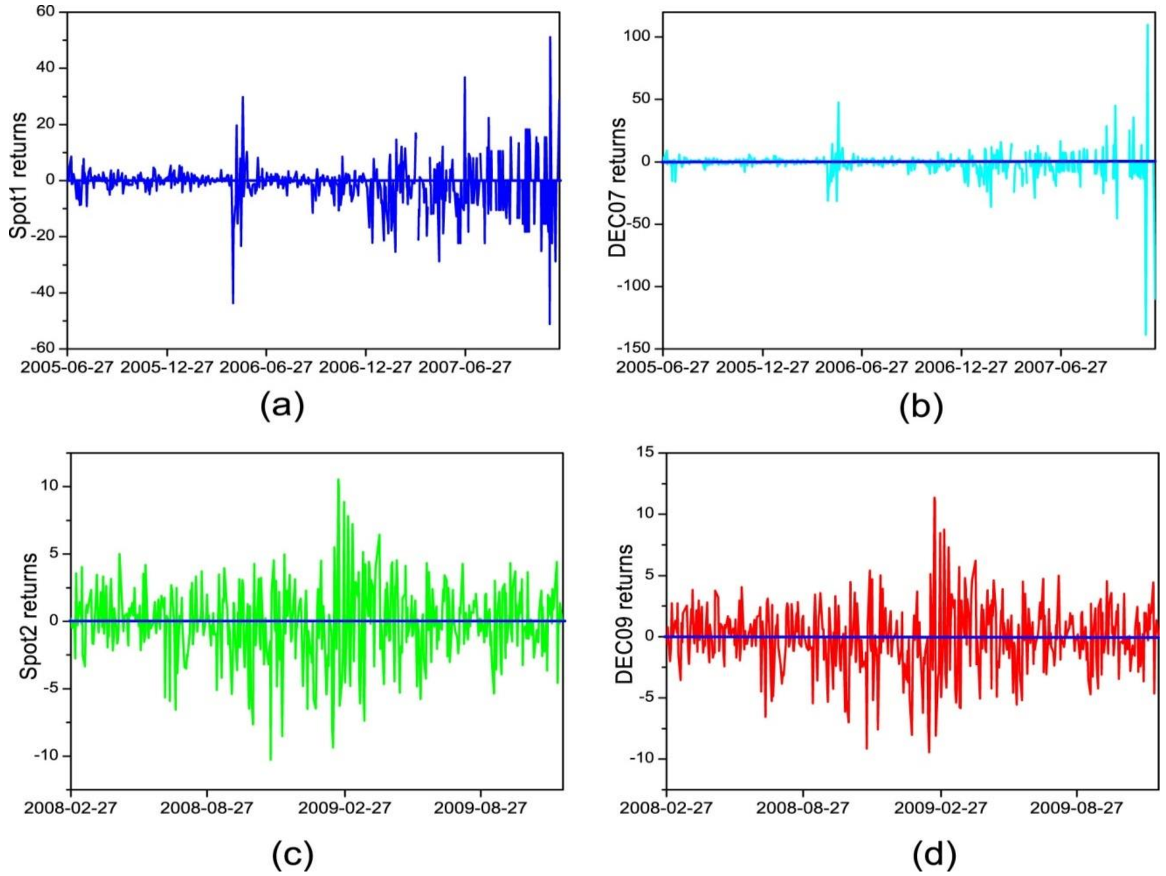

Fig. 2. Daily spot and futures price returns (100%) for the first and second phases.

Table1

Summary statistics for spot and futures returns during the sample period

Returns	Mean	SD	Skewness	Kurtosis	JB test	LB-Q(10)	ADF
Spot1	-0.9973	7.7354	-0.2956	12.4226	2369.50 (0.0000)	16.3730 (0.0890)	-6.6935 (0.0000)
DEC07	-1.2199	11.0586	-3.0604	71.6482	126272.00 (0.0000)	31.2950 (0.0010)	-4.7982 (0.0000)
Spot2	-0.0796	2.7572	-0.1389	4.3889	38.45 (0.0000)	32.5360 (0.0000)	-9.5304 (0.0000)
DEC09	-0.0911	2.7295	0.0146	4.6977	55.26 (0.0000)	26.9240 (0.0030)	-11.7053 (0.0000)

Note: Trend term is not included in the ADF test; p-values for corresponding null hypotheses are reported in parentheses.

5.2 Static VaR analysis for carbon returns

The returns were used to calculate the upside VaR. Returns were changed into a loss series to calculate the downside VaR. We first analyzed the EU ETS upside risk. According to Eq.(14), we obtained the mean excess for Spot1 returns. Eq.(7) defining the GPD and the maximum likelihood estimation of Eq.(8) yield the relevant GPD parameters. The results for Spot1 are shown in Fig. 3.

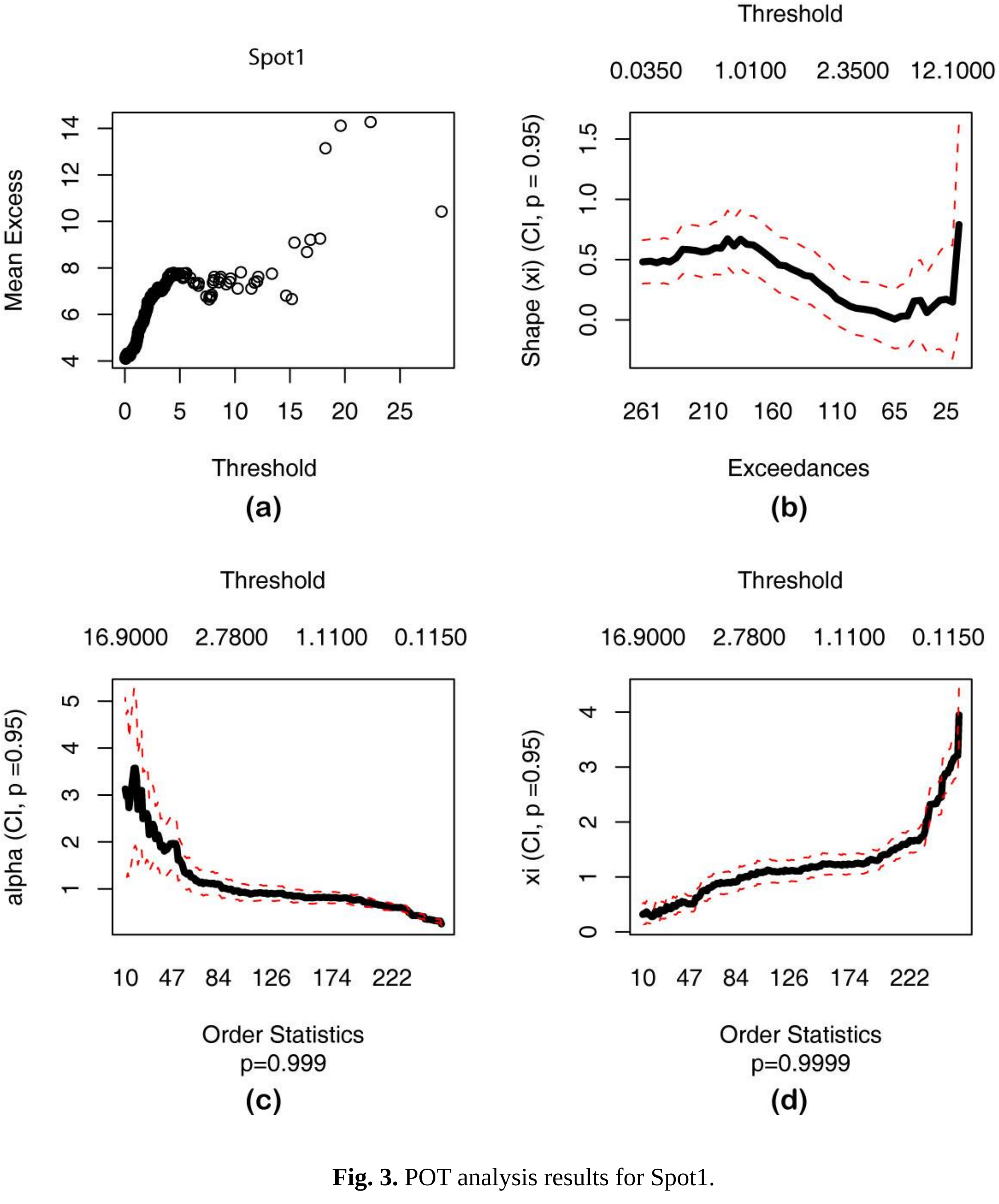

Fig. 3. POT analysis results for Spot1.

Choosing the threshold is very important. By increasing the number of observations for the series of maxima (a lower threshold), some observations from the centre of the distribution are introduced in the series, and the index of the tail is more precise but biased (i.e., there is less variance). By contrast, choosing a high threshold reduces bias but makes the estimator more volatile. As observed in Fig. 3, The first phase for spot process (Spot1) exhibits a Pareto distribution and the mean excess is positive, indicating a heavy-tailed distribution, which indicates the parameter should be $\xi > 0$. The curve in Fig. 3 tends to an asymptotic line that fits the GPD distribution. Fig. 3b is the maximum likelihood estimate of the shape parameter at a confidence level of 95%. When the number of extreme points is between 60 and 100, the shape estimator is asymptotically stable. As observed in Fig. 3, the threshold of 4.9 is a reasonable choice. There are 61 extreme points in the up-tail for Spot1 price returns.

After estimating the relevant GPD parameters, the results need to be tested. Tail parameters on fitting verify the accuracy of the threshold choice. The results are shown in Figs. 4 and 5.

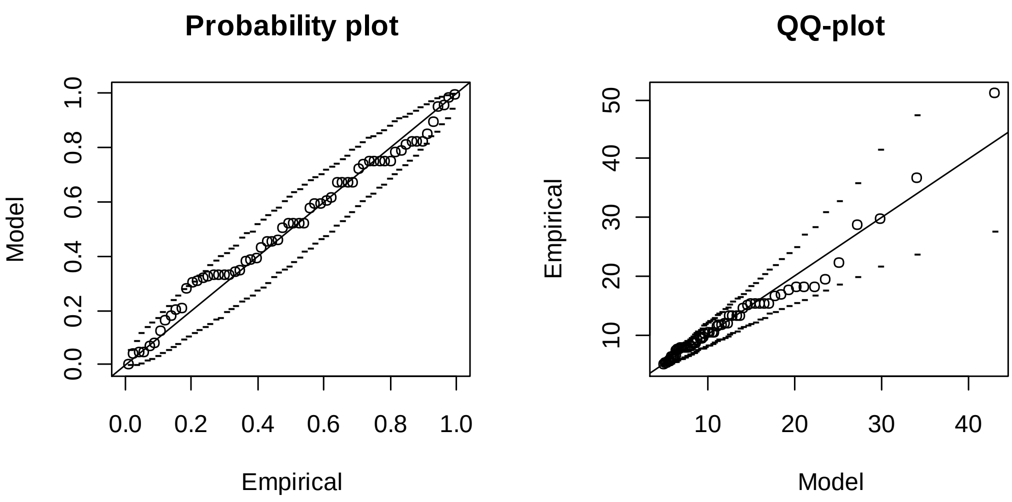

Fig. 4. Empirical distribution and QQ plot analysis of the Spot1 up-tail test.

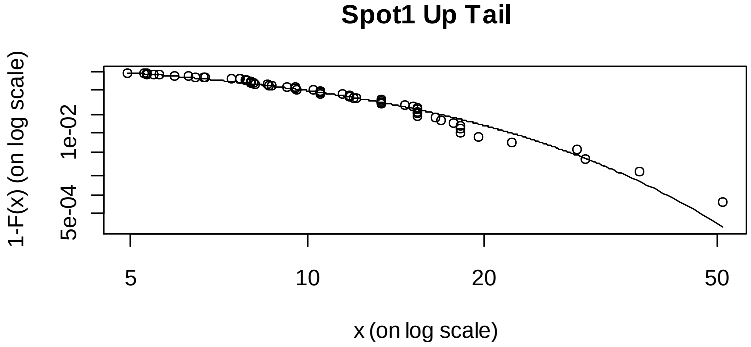

Fig. 5. Spot1 up-tail fitting under GPD.

The empirical distribution and QQ plot analysis reveal that the Spot1 up-tail test is acceptable according to the threshold selected (Fig. 4). Fig. 5 shows that the EVT model fits actual Spot1 returns well. Fitting of sample points on the up-tail falls on the GPD tail function, which is almost a straight line. There are fewer than six deviation points and the error rate is very low, indicating that the threshold meets the requirements. The results for Spot1 prices and other price returns are shown in Table 2.

Table 2

Estimation results for EVT models of carbon price returns

	Spot1		DEC07		Spot2		DEC09	
	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail
μ	4.9480	7.8988	5.1293	12.0953	3.7313	3.5784	3.1087	3.3829
ξ	0.0100	0.0626	0.3977	0.5365	0.1996	-0.3107	0.0586	-0.2609
β	7.6882	6.5130	5.3323	6.9767	1.2436	2.6353	1.7211	2.2730
N_u	61	81	51	36	30	40	39	47

In research on financial markets, it is common to analyze the overall risk situation while ignoring the risk of extreme events. Extreme events can lead to rapid price volatility, resulting in huge losses for traders. Therefore, use of EVT in market risk management is of great practical significance; in particular, VaR must be taken into account for bank risk management instruments under the Basel II Accord. Comparison of VaR and EVT results can reveal which method is better in describing carbon market risk.

According to Eqs. (12) and (13), we obtained the upside VaR and upside ES for the threshold selected. The results are shown in Fig. 6.

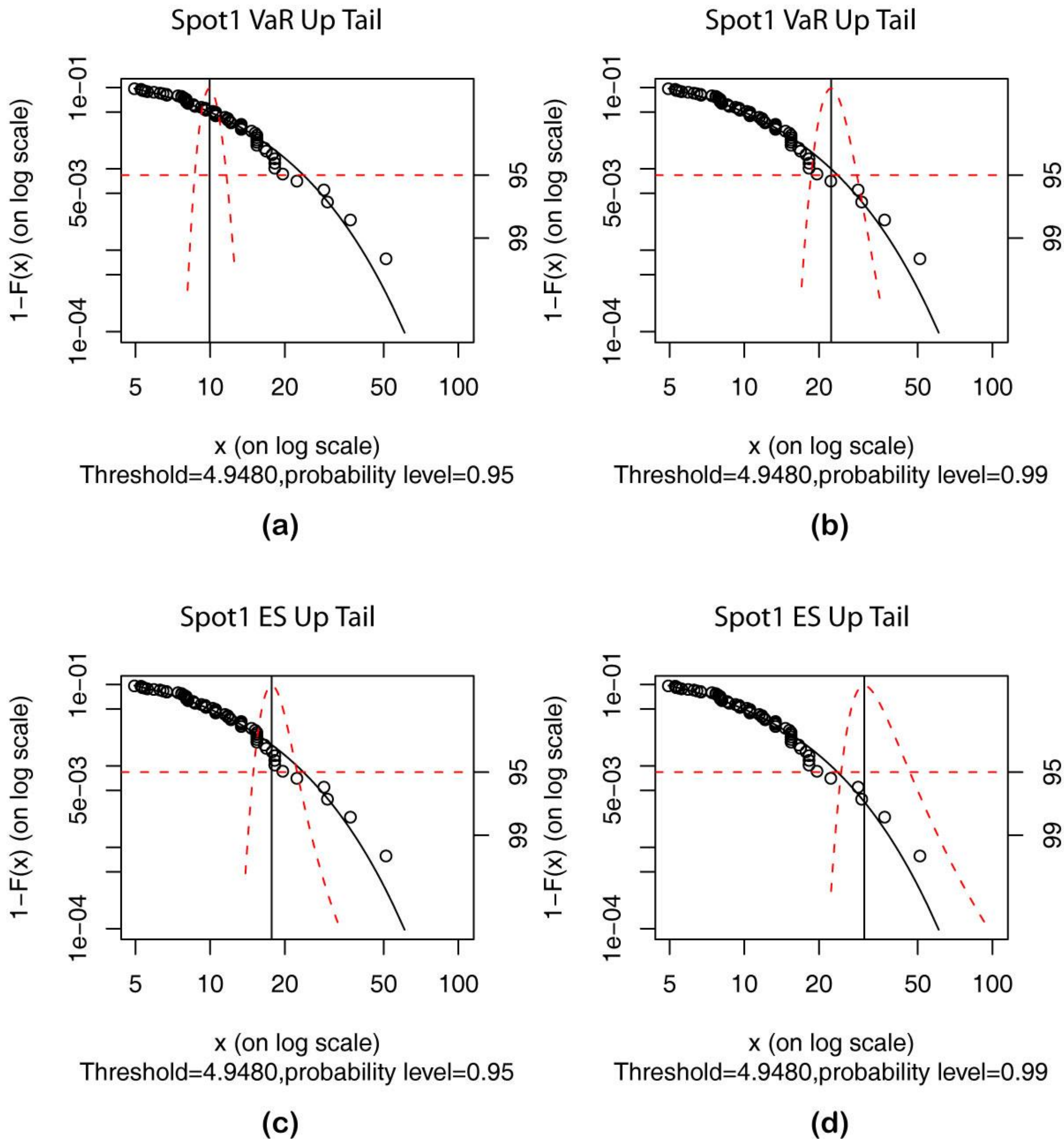

Fig. 6. Upside VaR and ES of EVT for Spot1 during 2005–2007.

Fig. 6a shows that the VaR is 9.9482 at a confidence level of 95% and a threshold of 4.9480, as denoted by the vertical line. The dotted line denotes the 95% confidence level and curves represent the confidence interval range. The economic meaning of this result is that the possibility that a loss due to changes in the carbon spot price will not exceed 9.9482% was 95% in 2005–2007. Fig. 6b shows the VaR at a confidence level of 99%. Fig. 6c,d shows ES at confidence levels of 95% and 99%, respectively, as a measure of conditional expected losses in excess of VaR.

The upside and downside VaRs and ESs based on EVT are shown in Table 3. We use the likelihood ratio LR test proposed by Kupiec [40] to back test VaR and the results for the traditional normal distribution are shown for comparison.

Table 3

Results for VaR model estimation and tests for carbon returns

	Spot1		Dec07		Spot2		Dec09	
	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail
				VaR				
$VaR_{95\%}$	9.9482	14.1484	7.8800	12.9668	4.0706	4.9183	4.0318	4.8649
$ES_{95\%}$	17.7646	21.5137	18.5495	29.0278	5.7090	6.6112	5.9175	6.3609
$VaR_{99\%}$	22.5031	25.8394	22.3681	31.9953	6.5596	7.7286	7.0217	7.3440
$ES_{99\%}$	30.4463	33.9854	42.6041	70.0818	8.8186	8.7554	9.1001	8.3271
				Back testing				
$LR_{95\%}$	0.0432	0.3182	0.0007	0.3182	0.1782	0.0452	0.0464	0.1782
$LR_{99\%}$	1.0265	1.0265	0.0221	0.3214	0.0342	0.0827	0.0342	0.3927

The results in Table 3 show that EVT models adequately estimate the VaRs for carbon price returns. With the exception of the upside and downside risks at confidence levels of 95% and 99%, all the LR statistics are less than the corresponding critical values. Therefore, according to the back testing method provided by Kupiec (1995), it can be argued that EVT models adequately estimate the VaRs for carbon price returns. Using the traditional method (see in Appendix A), estimates of upside and downside VaRs are not precise because the returns follow a non-normal distribution. Table 3 shows that the traditional method tends to overestimate the VaR at the 95% confidence level and underestimate the VaR at the 99% confidence level. Because the distribution is leptokurtic with a fat tail, EVT fits the returns better. Comparison reveals that the LR statistics for EVT are less than or equal to those for the traditional VaR, indicating that the static VaR estimate with EVT is sufficient for the sample data. For extreme events, ES is better than the VaR since it can estimate the actual market risk. If the market has an extreme event (subject to quota allocation effects, DEC07 prices fell in 2007), the gap between ES and VaR is large. The downside ES for DEC07 is 2.24-fold greater than that of VaR at the 95% confidence level and 2.19-fold that at the 99% confidence level, whereas for DEC09 the ES and VaR are very close at both confidence levels. Therefore, if there is extreme risk in the market, considering VaR alone will underestimate risk, whereas the ES can calculate the average loss above VaR expectations. The VaR combined with EVT can estimate the real market risk.

As the returns series are time-varying, we combined the static method with the dynamic characteristics of the returns series to estimate the dynamic VaR.

5.3 Dynamic VaR analysis for carbon price returns

5.3.1 Estimation of GARCH-type models for carbon price returns

To filter out the autocorrelation of carbon returns, the ARMA model was used. According to censored autocorrelation orders and graphs of partial autocorrelation functions, as well as the principle that the AIC value must be relatively minimum, an ARMA (1, 1) model was singled out after numerous trials. The carbon returns series exhibit significant volatility clustering, so an ARCH LM test was carried out for the residual series of the ARMA (1, 1) model. The results show that there are high-order ARCH effects, so GARCH models need to be adopted. The empirical results imply that there are significant TGARCH effects, so a TGARCH model was used. Considering the fat tail of the returns and the AIC value, some new distribution such as mixed-normal and mixed-stable was used instead of normal [47]. In the article, a GED distribution was introduced to depict the residuals of the GARCH model.

The results for Spot1, DEC07, Spot2 and DEC09 are shown in Table 4.

ARCH-LM tests results for residual series of the mean equation confirm that Spot1, Spot2 and DEC09 exhibit no volatility clustering, in contrast to DEC07.[3] The Q^2 statistics have large significance probabilities (both >10%), indicating that the goodness-of-fit of the models for returns is acceptable. Using the probability density function for GED, we calculated its 95% and 99% quantiles under the given parameters. The results in Table 4 show that the 95% quantile is close to that of the standard normal distribution (1.645), whereas the 99% quantile is greater than that of the standard normal distribution.

Table 4

Estimation results for GARCH and TGARCH models for carbon price returns

Parameter	Spot1(TGARCH-N)	DEC07(TGARCH-N)	Spot2(GARCH-GED)	DEC09(GARCH-GED)
Mean equation				
AR(1)	—	-0.3989 (0.0002)	—	—
MA(1)	0.1253 (0.0034)	0.6481 (0.0001)	0.0901 (0.0618)	0.1225 (0.0122)
Variance equation				

[3] For DEC07, we found that TGARCH-GED can eliminate volatility clustering, but the GARCH model does not meet the wide-smooth requirement, so we used a TGARCH-GED model. Choice of a suitable GARCH model for DEC07 should be investigated in future research.

α_0	0.4569 (0.0000)	0.3046 (0.0000)	0.1753 (0.0785)	0.2750 (0.0679)
α_1	0.1245 (0.0001)	0.1265 (0.0000)	0.0778 (0.0106)	0.1101 (0.0044)
β_1	0.7449 (0.0000)	0.7791 (0.0000)	0.8996 (0.0000)	0.8525 (0.000)
φ	0.3442 (0.0000)	0.3189 (0.0000)	—	—
GED	——	——	1.5724(0.0000)	1.6894(0.0000)
AIC	6.0594	6.1287	4.6935	4.6536
Log likelihood	-1927.9510	-1945.9880	-1074.5130	-1065.3260
		Quantiles		
Parameter	2.0000	2.0000	1.5724	1.6894
95%	1.6449	1.6449	1.6524	1.6511
99%	2.3263	2.3263	2.4684	2.4244

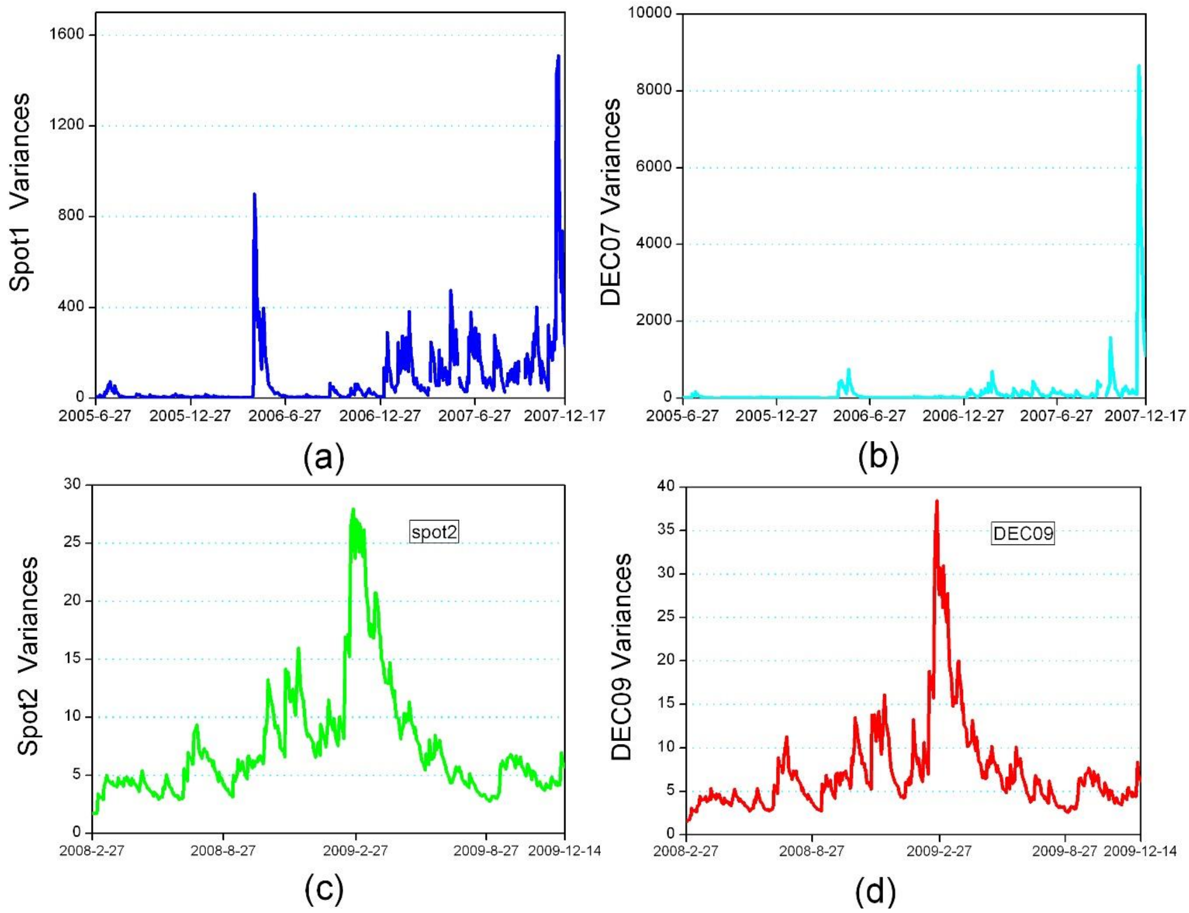

Fig. 7. Conditional variances for carbon price returns.

To compare the extent of volatility, Fig. 7 shows trends for the conditional variance for carbon returns. Volatility levels for Spot1 and DEC07 returns differ; volatility is greater for DEC07 than for Spot1 returns. Volatility levels for Spot2 and DEC09 returns are close, although the volatility for DEC09 returns is slightly greater on occasions. Returns for the second phase exhibit a trait whereby the greatest variance during periods with high volatility is more than 60-fold greater than the variance for the average volatility level. The variance for DEC07 is almost 1000-fold greater than that in the second phase. This type of large-scale volatility vibration demonstrates the extreme risk in the international carbon market.

5.3.2 Dynamic VaR model estimation and test for carbon returns

According to the GARCH models, we established EVT using residuals from the GARCH model and the results are shown in Table 5.

Table 5

EVT model estimation results for carbon price return residuals

	Spot1		DEC07		Spot2		DEC09	
	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail
μ	0.7055	1.3919	1.1160	1.4258	1.3134	1.1458	1.2177	1.2623
ξ	0.0367	0.1102	-0.0386	0.2163	-0.1530	-0.1987	-0.0555	-0.2497
β	0.5614	0.7139	0.7109	0.7379	0.4630	0.8478	0.3919	0.8874
N_u	92	56	37	51	37	54	46	45
$VaR_{95\%}$	1.3118	1.8064	1.2222	1.7915	1.5257	1.8114	1.4842	1.8107
$VaR_{99\%}$	2.2795	3.1140	2.3252	3.3643	2.1399	2.7970	2.0468	2.8053

Based on Eqs.(14) and (15), the upside and downside VaRs for carbon returns can be obtained at confidence levels of 95% and 99%. The results for DEC09 are shown in Figs. 8 and 9, with summary statistics in Table 6.

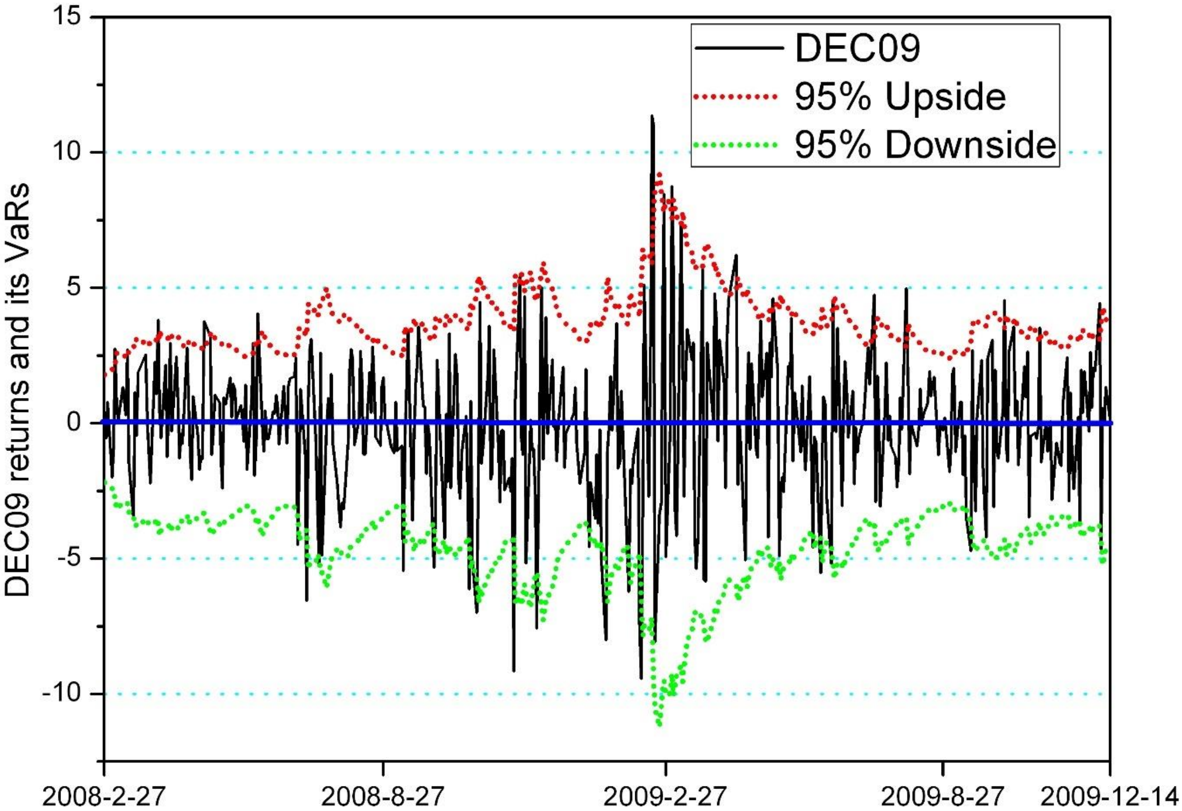

Fig. 8. DEC09 returns and VaRs at a confidence level of 95%.

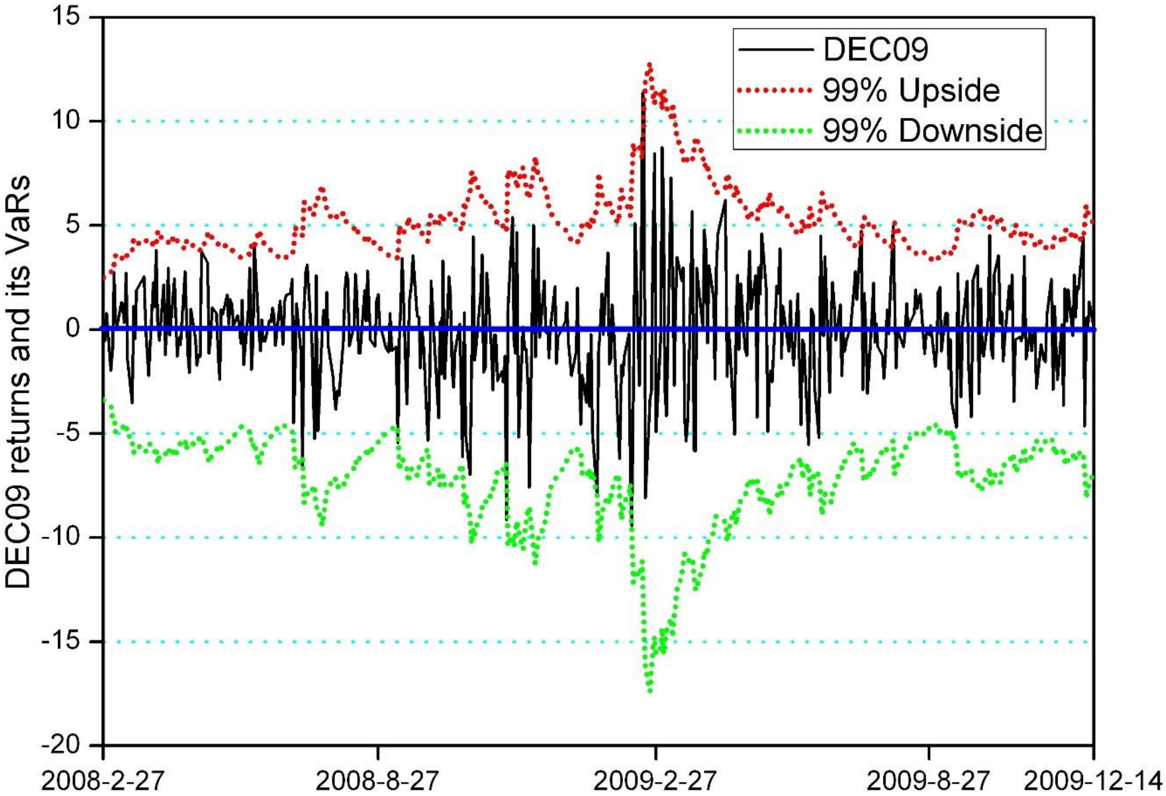

Fig. 9. DEC09 returns and VaRs at a confidence level of 99%.

According to the results, the dynamic VaR provides a better fit to carbon price changes. When the returns change a lot, VaR fluctuations are also violent. Figs. 8 and 9 show that the dynamic VaR based on GARCH-EVT provides a very good fit to actual changes in returns.

The dynamic VaR based on GARCH and EVT adequately estimates the risk for carbon price returns. Using DEC09 as an example (Table 6), Figs. 8 and 9 reflect the failure time. The numbers of upside and downside failure times are 21 and 24 at a confidence level of 95%, and 6 and 5 at a confidence level of 99%, respectively. The numbers of failure times are approximately 23 and 5 at confidence levels of 95% and 99%, respectively, so we can accept the results. According to Eq.(16), the upside and downside LR values are 0.1883 and 0.4552 at a confidence level of 95% and 0.3927 and 0.0342 at 99%, respectively, which are less than the critical value at the 95% (3.84) and 99% (6.64) levels. The dynamic VaR model here might underestimate the real DEC09 risk. As observed in Table 6, all the upside and downside LR values for Spot1, DEC07 and Spot2 are less than the critical value, confirming that the dynamic VaR model based on GARCH-EVT can estimate the real carbon market risk. In additional, all the LR values are very small, indicating that estimates of the upside and downside VaRs for carbon returns are very precise.

Table 6

Summary of dynamic VaRs for carbon price returns

	Conf. level	Risk type	Mean	SD	Max	Min	The number of failure times	Rate of failure	LR statistic
Spot1	95%	Upside	8.8878	7.5696	50.1547	1.8067	34	0.0533	0.1426
		Downside	-12.4341	10.5899	-2.5276	-70.1669	31	0.0486	0.0270
	99%	Upside	15.3279	13.0545	86.4967	3.1158	7	0.0094	0.0233
		Downside	-21.4348	18.2557	-4.3572	-120.9586	6	0.0094	0.0233
DEC07	95%	Upside	9.5544	11.9055	113.7213	1.5716	30	0.0471	0.1152
		Downside	-14.0048	17.4511	-2.3037	-166.6926	30	0.0471	0.1152
	99%	Upside	18.1769	22.6499	216.3515	2.9900	8	0.0126	0.3897
		Downside	-26.2999	32.7719	-4.3262	-313.0360	9	0.0141	0.9722
Spot2	95%	Upside	3.9936	1.1897	8.0645	1.9872	22	0.0478	0.0464
		Downside	-4.7414	1.4125	-2.3594	-9.5747	23	0.0478	0.0464
	99%	Upside	5.6013	1.6687	11.3111	2.7872	7	0.0152	1.0906
		Downside	-7.3213	2.1810	-3.6431	-14.7843	4	0.0087	0.0827

DEC09	95%	Upside	3.8094	1.2050	9.1981	1.7916	21	0.0457	0.1883
		Downside	-4.6474	1.4701	-2.1858	-11.2215	24	0.0522	0.0452
	99%	Upside	5.2996	1.6764	12.7963	2.4925	6	0.0130	0.3927
		Downside	-7.2002	2.2777	-3.3864	-17.3854	5	0.0109	0.0342

As observed in Table 6, downside risks are higher than upside risks in the spot and futures markets in both the first and second phases. In the first phase, the average upside risk is 15.33% and the maximum loss value is 86.49%, whereas the mean downside risk is 21.43% and the maximum loss value is 120.96% at a confidence level of 99%. For the futures market, downside risks are also higher than the upside risks. Therefore, the loss for price decreases is greater than that for price increases for investments in the carbon market.

Both upside and downside risks in the first phase are higher than in the second phase. The average upside risk for Spot1 is 21.43% and the maximum loss value is 120.96%, whereas the mean downside risk for Spot2 is 7.32% and the maximum loss value is 14.78% at a confidence level of 99%. In the futures market, the average upside risk for DEC07 is 26.30% and the maximum loss value is 313.03%, whereas the mean downside risk for DEC09 is 7.21% and the maximum loss value is 17.39% at a confidence level of 99% (Table 6). One of the reasons is the carbon price decreases from €20/ton to €0.02/ton, which leads to a large fluctuation in carbon price returns. Thus, investment in the market would be highly risky.

The risk for the spot market is similar to that for the futures market in the same phase. The upside and downside risks for the spot market are similar to those for the futures market in the first and second phases at confidence levels of 95% and 99% (Table 6).

5.3.3 Comparison of dynamic VaR models

According to Eqs. (14) and (15), we calculated the upside and downside VaRs based on GARCH at confidence levels of 95% and 99%. The results are shown in Table 7.

Table 7

Summary of VaRs based on a GARCH model

	Conf. level	Risk type	Mean	SD	Max	Min	The number of failure times	Rate of failure	LR statistic
Spot1	95%	Upside	11.3224	9.6432	63.8937	2.3016	17	0.0266	8.7640
		Downside	-11.3224	9.6432	-2.3016	-63.8937	36	0.0564	0.5335
	99%	Upside	16.0128	13.6378	90.3616	3.2550	6	0.0094	0.0233
		Downside	-16.0128	13.6378	-3.2550	-90.3616	20	0.0313	18.7584
DEC07	95%	Upside	12.8588	16.0231	153.0520	2.1152	19	0.0298	6.3402
		Downside	-12.8588	16.0231	-2.1152	-153.0520	37	0.0581	0.8351
	99%	Upside	18.1855	22.6606	216.4539	2.9914	8	0.0126	0.3897
		Downside	-18.1855	22.6606	-2.9914	-216.4539	20	0.0314	18.8020
Spot2	95%	Upside	4.3252	1.2885	8.7342	2.1523	16	0.0348	2.4986
		Downside	-4.3252	1.2885	-2.1523	-8.7342	28	0.0609	1.0732
	99%	Upside	6.4611	1.9248	13.0474	3.2151	2	0.0043	1.8832
		Downside	-6.4611	1.9248	-3.2151	-13.0474	12	0.0261	8.3333
DEC09	95%	Upside	3.2151	1.3405	10.2324	1.9931	16	0.0348	2.4986
		Downside	-3.2151	1.3405	-1.9931	-10.2324	29	0.0630	1.5273
	99%	Upside	6.2225	1.9684	15.0248	2.9266	2	0.0043	1.8832
		Downside	-6.2225	1.9684	-2.9266	-15.0248	10	0.0217	4.7949

The results reveal that, on the one hand, the VaR model under GARCH does not adequately measure the carbon market in the first phase. The critical χ^2 value at the 95% and 99% confidence level is 3.84 and 6.64, respectively. LR values for Spot1 upside and downside VaR at the 95% confidence level are greater than the critical value. On the other hand, all the failure rates for the second phase in Table 7 are less than the critical values for confidence levels of 95% and 99%. Therefore, the VaR model can estimate market risk in the second phase.

The dynamic VaR based on GARCH and EVT is more precise than the VaR based on GARCH for carbon spot and futures markets. Even if the upside and downside VaR models for carbon returns seem acceptable in terms of their LR value, their counterparts in Tables 6 and 7 seems more precise owing to smaller LR values. Consequently, we argue that overall it is more acceptable to use VaR models based on GARCH and EVT than those based only on GARCH.

6 Conclusions

Static VaR and dynamic VaR with EVT were used to measure risk in spot and futures carbon markets. A number of conclusions can be drawn from the results.

(1) Volatility levels differ for Spot1 and DEC07 returns; volatility is greater for DEC07 than for Spot1 returns. Volatility levels for Spot2 and DEC09 returns are close. The greatest variance during the second phase with high volatility is more than 60-fold greater than the variance for the average volatility level. The greatest variance for DEC07 is almost 1000-fold greater than that in the second phase. This type of large-scale volatility vibration demonstrates the extreme risk in the international carbon market.

(2) GPD provides a suitable fit for the asymmetric distribution tail for price increases and decreases. In the descriptions of EU ETS returns with an asymptotic distribution tail, the EVT method yielded incremental estimation of the distribution tail for carbon price returns. The GPD distribution provided a good fit to the price returns distribution. The significance of this approach is obtaining the corresponding quantiles, which are basic parameters for market stabilization and risk management. The existing literature does not specifically describe the EU ETS distribution tail and assuming that the entire sample fits a normal distribution to describe the tail leads to biased results.

(3) EVT models adequately estimated the VaRs for carbon price returns. For extreme events, ES is better than VaR because it can estimate the actual market risk. In both in the first and second phases, at confidence levels of 95% and 99%, static VaR based on EVT is more precise than the traditional VaR. The dynamic upside and downside VaRs based on GARCH-EVT are more precise than VaRs based on GARCH for carbon spot and futures markets.

(4) As the quota allocation mechanism natured, the carbon market became more standardized from the first phase to the second phase. For both spot and futures markets, VaR was significantly lower in the second than in the first phase. The decrease in volatility shock was slower in the second than in the first phase. An asymmetric leverage effect is more obvious in the first than in the second phase. The results demonstrate that the carbon market is becoming standardized and market risk is reducing, enhancing confidence in carbon trading. A prerequisite for development of the carbon market is rational quota allocation, which will have an impact on confidence in long-term market participation. In the context of banking and borrowing, the issue of price freezes in the carbon market may have been solved, but the banking and borrowing are still worth discussing because of carbon price in relation to reduction effects.

(5) Use of traditional risk assessment methods may lead to miscalculation of EU ETS market risk. Calculation of static and dynamic VaRs revealed that VaR based on EVT is better than traditional methods. Use of traditional risk management methods for the EU ETS could lead to significant errors in market risk estimates, because the EU ETS downside risk is greater than the upside risk. For EU ETS participants, appropriate use of EVT will enhance safe operation of the carbon fund. EVT does not require a distribution assumption for price returns, but lets the data fit a distribution tail, greatly reducing the model risk. EVT can effectively deal with the phenomenon of fat tails.

The EU ETS market has specific features and EU ETS carbon prices are affected by the following factors. EU ETS participants can control their own supply of emission rights, so actual reductions in emissions by different companies and their reduction policies have an impact on carbon prices. Moreover, emission allowances have a clear time limit and the EU ETS does not allow banking across the phase, which directly led to a carbon price approaching zero at the end of the first phase. This is an important difference between the EU ETS and the common financial market. EU ETS prices are extremely sensitive to changes in policy: international climate negotiations impact on the future form of global emission reductions expected and national allocation plans have a direct impact on EU ETS trading trends. In addition, EU ETS and Clean Development Mechanism (CDM) project-based market connections will also affect the supply and demand for carbon allowances. These factors all affect EU ETS risk and EVT can help EU ETS participants to face the risk from carbon price fluctuation.

(6) Regulators should be concerned about the effectiveness of market mechanisms in EU ETS policy. EU ETS regulators can develop and improve carbon market by considering the allowance allocation to avoid special events such as over allocation. Market participant are concerned about price changes especially in special events. Over-reaction phenomena, which lack objectivity, can reduce the effectiveness of stabilization policy mechanisms. EVT holds that the effect of policy on price depends not only on the speed at which information is transmitted, but also on the timing of policy implementation, investor sentiment and the price state. Therefore, a "good policy" may not lead to a "good result", either within the expected time or even at all. As mentioned above, the carbon price returns distribution, especially for price changes, is the basis of

EU ETS price behavior and market risk. The results of this study provide an empirical foundation for the effect of EU ETS market policies. For future study, we suggest to study the dependencies and integration of spot and future market risk via EVT and copula functions.

Appendix A Traditional VaR model estimation and tests for carbon returns

	Spot1		Dec07		Spot2		Dec09	
	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail	Up tail	Down tail
				VaR				
$VaR_{95\%}$	11.7275	13.7221	16.9715	19.4114	4.4560	4.6152	4.3990	4.5812
$ES_{95\%}$	18.5982	20.7726	44.7434	40.5201	6.4869	7.5640	6.0256	5.9732
$VaR_{99\%}$	16.9953	18.9900	24.5024	26.9423	6.3337	6.4929	6.2578	6.4400
$ES_{99\%}$	26.0713	26.6480	48.6788	59.6285	8.8940	8.0012	9.3835	7.9059
				Back testing				
$LR_{95\%}$	0.8179	0.5472	29.4950	10.0812	4.2839	8.0994	0.1883	1.5272
$LR_{99\%}$	1.7806	8.5522	0.0221	0.3897	0.0342	2.0796	0.0342	2.0796

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