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EDITED BY
Muhlis Can,
BETA Akademi-SSR Lab, Turkey

REVIEWED BY
Nurhan Toguc,
Istanbul Esenyurt Üniversity, Turkey
Ihsan Oluç,
Mehmet Akif Ersoy University, Turkey

*CORRESPONDENCE
Susheng Wang,
wangss@sustech.edu.cn

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Carbon market volatility analysis based on structural breaks: Evidence from EU-ETS and China

Haixu Yu[1], He Wang[1], Chuanyu Liang[1], Zhaohua Liu[1] and Susheng Wang[1,2]*

[1]School of Business, Southern University of Science and Technology, Shenzhen, China, [2]School of Economics and Management, Harbin Institute of Technology, Shenzhen, China

In recent years, carbon market transactions have become more active. The number of countries participating in carbon market regulation is increasing, and the carbon market's overall turnover continues to grow. It is important to study the features of carbon allowance price volatility for the stable development of the carbon market. This paper constructs a modified ICSS-GARCH model to analyze the volatility of carbon price returns and the dynamic characteristics of price fluctuations in the emissions trading system of the European Union (EU-ETS) and the Chinese carbon pilot markets in Hubei. The results show that fluctuations in carbon price returns have a leverage effect and that the impact of negative news on the market is stronger than that of positive news. The international climate and energy conferences, abnormal changes in traditional energy prices, and global public health emergencies all affect volatility and cause shocks to the carbon trading market. The modified ICSS-GARCH model with structural breaks can reduce the pseudovolatility of the return series to a certain extent and can improve the accuracy of the model. This research can give policymakers some implications about how to develop the carbon market and help market participants control the risks of fluctuations in carbon allowances. Regulators should enhance carbon price monitoring and focus on short-term shocks in the carbon market to reduce trading risks. The Chinese carbon market should strengthen the system design and develop carbon financial derivatives.

KEYWORDS

carbon market volatility, EU-ETS, ICSS algorithm, GARCH model, Chinese carbon market

1 Introduction

Countries around the world are taking steps to reduce emissions of greenhouse gases such as carbon dioxide because of climate change and other environmental and ecological problems (Can et al., 2022). To reduce carbon emissions, many countries have signed the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol and the Paris Agreement, etc. The Kyoto Protocol outlines the obligations of developed economies to reduce emissions and proposes three flexible mechanisms to reduce emissions, of which carbon trading is one (Can et al., 2021b). According to the International Carbon Action Partnership's (ICAP) Emissions Trading Worldwide Status Report 2021, there are currently 25 emissions trading system (ETS) in operation around the world, with another 22 scheduled to go operational in the near future. Carbon emissions trading will cover 17% of global emissions. The existing trading systems include EU emissions trading system (EU-ETS) and US trading system (RGGI), etc.

The EU-ETS was established in 2005 and is currently the world's largest and most active carbon emissions trading system. EU-ETS carbon allowances trading reaches 8,1 billion tons of carbon dioxide (CO_2) in 2020, representing approximately 90 percent of the total global carbon trading volume, with a trading volume of €20 billion. It has been implemented in four phases and is currently in its fourth phase. In the first three phases of EU-ETS development, the range of countries, industries and enterprises covered by trading gradually expanded, and the proportion of auctions in the allowance allocation process gradually increased (instead of free allocation). The major difference between the three phases is the change from grandparenting[1] to benchmarking[2] in the allocation of allowances, indicating the continuous maturation of the EU-ETS management system. In the EU-ETS, the turnover of EUAs is higher than that of other trading varieties, such as certified emission reductions (CERs). EU allowance (EUA) futures allow carbon credits to be traded on commodity futures exchanges, such as soybeans, oil, and other commodities. The EU-ETS has become the world's largest carbon futures market, with over 90% of the total volume traded in the EU carbon market (Lamphiere et al., 2021). The carbon futures market has made the market more open and has become a model for other countries and regions.

According to the International Energy Agency (IEA), China's carbon emissions exceed 11.9 billion tons in 2021, covering about one-third of the world's carbon emissions. The Chinese government announced at the Paris Climate Conference that CO_2 emissions will peak around 2030 and then decline by 60–65 percent compared to 2005. China is exploring the use of market mechanisms to reduce greenhouse gas emissions in response to the pressures of CO_2 emission reduction and sustainable development. As an important developing country and CO_2 emitter, China expects that the carbon market will help achieve its emissions reduction objectives and reduce the global greenhouse effect at the lowest economic cost among the available emission reduction policies (Liu et al., 2015; Gozgor and Can, 2017). Since 2013, China has initiated eight regional carbon market pilots in Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing, and Fujian (Ren and Lo, 2017). The pilot markets have been operational for only a short period, and there are still some unstable factors in the carbon market (Zhao et al., 2016). The carbon market in China covered about 3,000 emitting enterprises in the steel, electricity, and cement industries, establishing a large-scale market initially. China's carbon emissions trading market has grown to become the world's second largest, and it now plays an important role in the international energy trading market. Under these circumstances, it is more important and urgent to study how carbon prices change in both the EU-ETS market and the Chinese carbon market.

Both the EU carbon market and the Chinese carbon pilot cover significant emission sectors such as industry and power. However, because of the different development processes, there are many differences between the two markets. The major variation is in the allocation of carbon allowances. The auction is employed in the EU-ETS, with the European Commission determining the overall number of carbon allowances and allocating them to each member. The auction method ensures the scarcity of carbon allowances. The Chinese carbon market adopts the free allocation approach and is susceptible to surplus. Both the EU-ETS and Chinese markets have excess carbon allowances, leading to a carbon price failure. The Chinese market is particularly affected. Chinese carbon credits can only be traded on the spot market. The diversity of carbon financial instruments and trading activity is restricted compared to the EU-ETS.

In recent years, the effectiveness of carbon markets, the volatility and risk assessment of carbon prices, and the spillover effects between carbon markets and traditional energy markets have been hot topics (Benz and Truck, 2009; Chevallier, 2009; Zhang and Sun, 2016; Chang et al., 2017; Zhao et al., 2020; Can et al., 2021a). In prior studies, time series of financial asset markets, such as the stock market or crude oil market, and structural breaks have been widely studied as the iterative cumulative sum of squares (ICSS) algorithm for detecting breaks is now well established (Malik and Hassan, 2004; Malik et al., 2005; Wen et al., 2018). However, less research has been conducted on structural breaks in carbon markets. Price volatility in the carbon market is influenced by external factors such as political change, climate change, and allowance allocation. External factors cause carbon price instability and risk spillover. Moreover, exploring the reasons and mechanisms of structural breaks is important for carbon market policymakers to effectively adjust market policies. In this paper, we adopt the modified ICSS algorithm to investigate the structural breaks in carbon market returns and add structural breaks as a dummy variable in the model to estimate the volatility characteristics of the EU-ETS and the Chinese carbon market.

The current research on carbon market volatility is mainly focused on the EU-ETS. In the existing literature, the volatility of

1 Grandparenting allows covered enterprises to get emission permits based on their previous emissions within a base year or base period.

2 Benchmarking rewards efficient installations and can more easily assimilate new entrants.

carbon prices, the factors influencing carbon prices, the effectiveness of carbon markets, and the measurement of risk in carbon markets have been examined. Benz and Truck (2009) and Daskalakis et al. (2009) analyzed the European carbon market and found that emission allowance returns exhibit skewness, excess kurtosis, and volatility clustering. Byun and Cho (2013) used the GARCH model to estimate the price volatility of carbon futures prices. Dutta (2018) used the GARCH-jump model to investigate the volatility of the EU-ETS prices and provide recommendations to investors and policymakers. Guo et al. (2018) used the GARCH model to analyze the impact of the EU-ETS emission announcements in phases I and II on trading behavior and prices. The findings confirm the maturity of the EU-ETS in phase II. Fan et al. (2017) analyzed the impact of 50 policy announcements from the EU ETS on carbon prices. The aggregate impacts of the 50 events studied were small, and only sections of the policies impacted carbon prices. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and they impact the demand and supply of carbon permits through trading, which influences carbon pricing (Wang et al., 2019). Zhang et al. (2018) adopted the EGARCH model to examine the price of carbon pilot markets in China and discovered a long memory in the sequence of carbon price returns. Zhao et al. (2016) demonstrated that the market efficiency of ETS pilots in China is not satisfactory, although ETS system designs have achieved some promising preliminary results.

In this paper, we compare the price of EUA futures, the most actively traded variant in the EU-ETS, with the spot price of the Chinese carbon pilot market and analyze the price fluctuations in the carbon market. This paper makes the following contributions to the existing literature: Firstly, to the best of our knowledge, prior studies have concentrated on the value-at-risk of the carbon market while disregarding the impact of structural breaks on risk assessments, thus making carbon market risk underestimated (Zhang et al., 2018). Our research is a useful supplement. Secondly, we noticed that policy announcements and important events can cause structural changes in carbon price returns, which can have an impact on the carbon market or create market risks. We detect the structural change points by using the modified ICSS algorithm. We then use the structural change points as dummy variables to study how event shocks affect the volatility of the carbon market. This is a novel approach in the study of carbon market volatility to incorporate structural breaks estimated by the modified ICSS algorithm into carbon market volatility research. Furthermore, we explore the asymmetry of the carbon price. This is an extension of the study of the characteristics of carbon market prices. The findings confirm that carbon price returns are also asymmetrical and that the impact of positive and negative news on the carbon price varies, which is similar to those of other financial assets. These important results and conclusions will be used to make important suggestions about how the carbon finance market will grow in the future and how governments and market participants will manage such a market and invest in it.

The remainder of this paper is structured as follows. Section 2 is a literature review. Section 3 introduces the methodologies used in this paper. Section 4 reports the empirical results. Section 5 provides further discussion on EU-ETS futures in phase II and provides policy recommendations. Section 6 provides the conclusions of the paper.

2 Related literature

2.1 Carbon price volatility

In previous papers, time series of financial asset markets, such as the stock market or crude oil market, with structural breaks have been widely studied with the iterative cumulative sum of squares (ICSS) algorithm for detecting breaks now well established (Malik and Hassan, 2004; Malik et al., 2005; Wen et al., 2018). However, less research has been done on structural breaks in carbon markets.

The carbon market is an emerging financial market. Existing literature on carbon markets is mainly focused on carbon prices, including carbon market volatility, factors influencing carbon prices, carbon market effectiveness, and carbon market risk measurement.

For example, Benz and Truck (2009) and Daskalakis et al. (2009) analyzed the European carbon market and found that emission allowance returns exhibit skewness, excess kurtosis, and volatility clustering. Byun and Cho (2013) estimated the volatility of carbon futures prices using IV, k-NN, and GARCH-type models. The results indicate that the GJR-GARCH model offers the most information on the volatility of carbon futures. Paolella and Taschini (2008) found asymmetries in the spot carbon price, which are essential for risk management in the carbon market. Dutta (2018) tested for extreme values in EUA and investigated the volatility of EU-ETS prices using the GARCH-jump model. The results demonstrate that the GARCH-jump model can capture discrete jumps in asset returns. Outliers and time-varying jumps play a crucial role in the risk management of the carbon market. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and impact the demand and supply of carbon permits *via* trading, which influences carbon pricing. Gorenflo (2013) investigates the price efficiency of EUA futures and spot. The results show that futures markets are better at finding prices than spot markets, with carbon futures playing a bigger role.

Numerous studies have examined the performance of the carbon market in China. For example, Zhang et al. (2018) adopted the EGARCH model to examine the price of carbon pilot markets in China and discovered a long memory in the

TABLE 1 Characteristics of the different phases of EU-ETS.

	Phase I (2005–2007)	Phase II (2008–2012)	Phase III (2013–2020)	Phase IV (2021–2030)
Emission allowances ($MtCO_2e$)	2096	2049	2084	1,610
Greenhouse gas	CO_2	CO_2 and N_2O	CO_2, N_2O and PFCs	CO_2, N_2O, and PFCs
Decline rate	—	—	1.74%	2.20%
Allowance allocation	Free allocation	10% of general allowances were auctioned off	57% of general allowances were auctioned off	57% of general allowances were auctioned off
Industry	Power sector	Power sector, Aviation sector	Expanded industrial sector	Consistent with Phase III

sequence of carbon price returns. Lyu et al. (2020) investigates the dynamic characteristics of volatility using the MCMC-SV model and Chinese carbon price returns in Hubei, Shenzhen, and Shanghai from 2015 to 2018. The results demonstrate that the Chinese carbon prices indicate an aggregation of volatility, although the long-term volatility is not highly cyclical. Zhao et al. (2016) demonstrated that the market efficiency of ETS pilots in China is not satisfactory, with huge price differences and insufficient liquidity across ETS pilots, although ETS system designs have achieved some promising preliminary results. This result was caused by the inappropriate allocation of allowances and the low motivation of businesses to trade. Liu et al. (2020) examined the operational efficiency of China's seven carbon markets, using a variance ratio test. The findings suggest that the markets in Hubei and Guangdong are weakly efficient, while the remainder of the markets are less efficient.

Prior research indicates that the modified ICSS model has been widely utilized in measuring the volatility of financial assets and is capable of analyzing the volatility of carbon market prices (Malik and Hassan, 2004; Wen et al., 2018). In addition, a comparative study of EU-ETS and Chinese carbon pilot markets could help the carbon market develop better.

2.2 EU-ETS and China carbon pilots

The EU Emissions Trading System (EU-ETS), established in 2005, is a carbon trading mechanism based on EU regulations and national legislation. The EU-ETS is the world's most developed carbon trading system and dominates the international carbon financial market. Currently, the EU-ETS is in its fourth phase, following three phases of development and gradual improvement. During previous phases of development, the carbon market's coverage of covered sectors and gases gradually expanded, and the proportion of auctions in the allowance allocation process gradually increased. Table 1 shows the difference between the different phases of EU-ETS.

In the EU-ETS, the turnover of EUAs is higher than that of other trading varieties, such as certified emission reductions (CERs). In this paper, EUA futures phase III prices are used

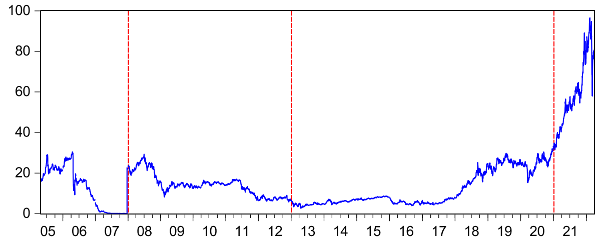

FIGURE 1
Price trends in EUA futures. The vertical lines mark the beginning of the different phases: phase I (2005–2007), phase II (2008–2012), phase III (2013–2020), and phase IV (2020–present).

to analyze the behavior of price volatility in the carbon market, while phase II prices are used for the comparative analysis. Figure 1 shows the price trend of EUA futures from 2005 to 2021.

The carbon market was immature during the first phase of the EU-ETS due to a lack of experience with relevant allocations. In the first phase, numerous factors affected the futures price, and there were significant price fluctuations. Because of the inability to store Phase I and Phase II allowances across phases, the EUA price fell to an all-time low of €0.01 at the end of 2007, undermining the effectiveness of the EU-ETS market. In the second and third phases, the European Commission revised the trading mechanism and the way allowances are allocated. Since 2008, EUA futures prices have shown regular changes, influenced by global economic trends and energy prices. The EU-ETS matured after the initial two stages of exploration and development. Thus, this paper analyzes the volatility characteristics of futures prices in the third stage.

As the main supplier of demand for clean development mechanism (CDM) projects, China participates in worldwide emission reduction missions. In 2013, China established eight regional ETS pilots. The pilots have different prices, turnover, and volumes. Figure 2 shows the price trend for the major pilots. The price trend of each carbon pilot in China is different, and the eight carbon market pilots have their own transaction rules and systems. Furthermore, most studies use trading data from the carbon pilots

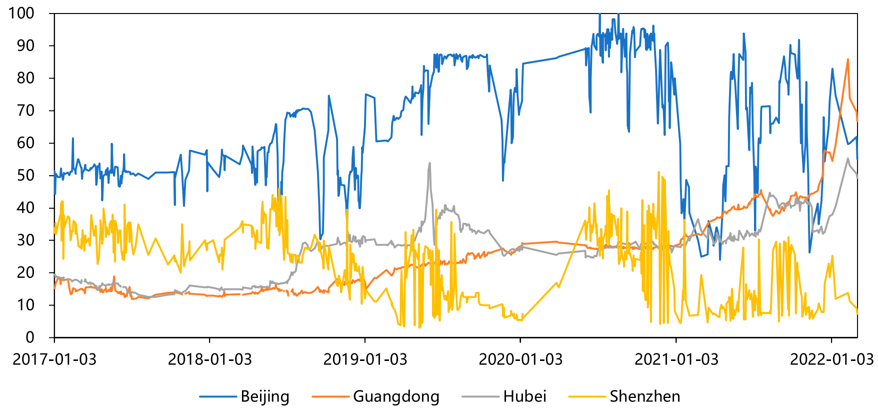

FIGURE 2
Price trends of major carbon pilots in China, including the Beijing, Guangdong, Hubei, and Shenzhen pilots.

in Shenzhen, Guangdong, and Hubei because these three pilots have higher market shares and liquidity than other carbon pilots (Fan and Todorova, 2017; Chang et al., 2018; Zhao et al., 2020). The Hubei spot price is used in this study because it is the largest market in terms of turnover and is relatively active and mature.

3 Methodology

3.1 Modified ICSS algorithm

The iterative cumulative sums of squares (ICSS) algorithm was proposed by Inclan and Tiao (1994). This method is used to distinguish structural break points of volatility based on the cumulative sum (CUSUM) test statistic. At the start of the process, the method assumes that the variance of the time series is the same for a certain period of time. The variance changes at the time of the unexpected event and then remains constant. There is a sudden structural change during an event. The procedure is as follows.

Assume that the sample has T observations and that the residual sequence of the sample $a_t \sim i.i.d.\, N(0, \sigma_t^2)$, with N_T structural variance points, can be divided into N_T +1 intervals. The sequence of structural mutation points is written as $\{k_1, k_2, \ldots \ldots k_{N_T}, \}$, $1 < k_1 < k_2 < \ldots < k_{N_T} < T$. Each interval's variance is denoted by σ_j^2, where $j = 0, 1, 2, \ldots, N_T$, i.e.,

$$\begin{array}{ll} \sigma_0^2 = a_0^2 & 1 < t < k_1 \\ \sigma_1^2 = a_1^2 & k_1 < t < k_2 \\ \sigma_{N_T}^2 = a_{N_T}^2 & k_{N_T} < a < T_1 \end{array} \tag{1}$$

$C_k = \sum_{i=1}^{k} \epsilon_t^2, k = 1, 2, \ldots \ldots, T$ represents the cumulative sum of squares of the return series up to moment k. Then, $C_T = \sum_{t=1}^{T} \epsilon_t^2$. Define IT as the statistic.

$$IT = \sup_k \left| \sqrt{T/2}\, D_k \right| \tag{2}$$

where $D_k = \frac{C_k}{C_t} - \frac{k}{T}$ and $D_0 = D_T = 0$ Assuming that _t is a normally distributed random variable that is distributed independently and identically at zero mean, the asymptotic distribution of the test statistic is

$$IT \Rightarrow \sup_k \left| W_r^* \right| \tag{3}$$

D_k follows a Brownian bridge process that fluctuates up and down around the zero axis if the sample is homoscedastic over the estimation period. If there is a structural change in the interval, D_k will deviate from zero and have a certain probability of crossing the boundary. A structural break point is considered to exist in the interval when $\sqrt{T/2}\mathrm{D_k}$ exceeds the upper and lower bounds of 1.358 at a 95% confidence interval.

The ICSS algorithm assumes that $\{\epsilon_t\} \sim i.i.d. N(0, \sigma^2)$ and that the variance in the subintervals is constant. The idea that returns from financial assets are normally distributed underpins many traditional financial theories, but the reality is that many (even most) assets do not conform to this assumption. Instead, empirical distributions exhibit higher peaks and fatter tails. Sanso and Malik thus proposed a modified ICSS algorithm. The modified test statistic is shown below (Sansó et al., 2004; Malik et al., 2005).

$$\kappa_2 = \sup \left| \frac{G_K}{\sqrt{T}} \right| \tag{4}$$

Previous research has shown that event shocks can cause structural break points in time series (Malik, 2003). Dummy variables incorporated into the model can reduce the pseudovolatility of the return series and improve model accuracy. The modified ICSS algorithm is used to detect structural break points in the following study. We use the news to determine which major events they correspond to and add them to the model as dummy variables.

3.2 GARCH model

Engle (1982) proposed the autoregressive conditional heteroskedasticity (ARCH) model for studying the volatility of asset prices. Bollerslev (1986) proposed the generalized ARCH (GARCH) model. The GARCH model adds the lagged values of the conditional variance across periods to the ARCH model to describe the long memory of financial assets. The GARCH (p, q) model is given by the following equation:

$$\begin{aligned} a_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{5}$$

where $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $0 < \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_i < 1$. These constraints on the coefficients ensure the nonnegativity of the variance. The GARCH (1, 1) model is by far the most commonly used model because it avoids a large number of delays that were previously associated with it, and thus it is our preferred model within the GARCH family of models.

3.3 Exponential GARCH model

Many studies have found a leverage effect in financial assets. The leverage effect is caused by the fact that negative returns have a greater impact on future volatility than positive returns (Christie, 1982). The exponential GARCH (EGARCH) model was proposed by Nelson (1991). On the left side of the model equation, the conditional variance is logarithmized. This model overcomes the critical limitation of GARCH models, which is parameter nonnegativity. The conditional variance equation of the EGARCH (1, 1) model is given by the following equation.

$$\ln(\sigma_t^2) = \alpha \ln(\sigma_{t-1}^2) + \beta \left| \frac{\mu_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\mu_{t-1}}{\sigma_{t-1}} + \omega \tag{6}$$

The $\frac{\mu_{t-1}}{\sigma_{t-1}}$ term replaces the μ_{t-1} term in the EGARCH model. It improves the model's ability to describe the effect magnitude and persistence. The model describes the asymmetry of volatility through the additional parameter. The leverage effect is achieved by the second and third terms on the right side of the equation.

If the coefficient of the asymmetric term $\gamma = 0$, there is no leverage effect. If the coefficient of the asymmetric term $\gamma < 0$, it means there is a leverage effect. This ensures that positive return shocks induce less volatility than negative return shocks (Engle and Ng, 1993). It is clear that negative shocks will have a larger effect on future volatility than positive shocks of the same size.

The normal distribution, which forms the basis of portfolio theory, may not necessarily apply to financial asset price patterns. Therefore, we assume that the residuals follow a generalized error distribution (GED) in the following analysis. The distribution is given by the following equation.

$$f(x|v) = \frac{v}{\lambda \times 2^{1+\frac{1}{v}} \times \Gamma\left(\frac{1}{v}\right)} e^{-\frac{1}{2} \times \left|\frac{x}{\lambda}\right|^{v}}, x \in (-\infty, \infty)\,(0 < v \leq \infty) \tag{7}$$

$$\lambda = \left[2^{-\frac{2}{v}} \times \frac{\Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)} \right]^{\frac{1}{2}} \tag{8}$$

where v is the degrees of freedom.

3.4 Modified ICSS-GARCH model

In this paper, we adopt the AR (1)-GARCH (1, 1) model to fit the EUA futures returns and MA (1)-GARCH (1, 1) to fit the Hubei spot returns. The ICSS-GARCH models used to describe the EUA futures returns and Hubei spot returns are shown in Eqs 9, 10, respectively.

$$\begin{aligned} r_t &= \phi_1 r_{t-1} + a_t \\ a_t &= \sigma_t \varepsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum_{k=1}^{n} d_k D_k \end{aligned} \tag{9}$$

$$\begin{aligned} r_t &= \theta_1 a_{t-1} + a_t \\ a_t &= \sigma_t \varepsilon_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum_{k=1}^{n} d_k D_k \end{aligned} \tag{10}$$

4 Empirical analysis

4.1 Data

In this paper, we collect a dataset of EUA futures prices and Hubei carbon spot prices. In this part, we use data on EUA futures from phase III. The sample period for EUA futures is from 1 January 2013, to 31 December 2020. The sample period for spot prices on the Hubei carbon market is from 1 July 2019, to 30 July 2021, encompassing two emissions trading compliance periods. The Chinese carbon market is still in the development stage. To better capture price fluctuations, we chose data from recent years. The logarithm of the prices is used to calculate all yield series data.

$$R_t = \ln Y_t - \ln Y_{t-1} \tag{11}$$

where Y_t represents the carbon price on day t, Y_{t-1} represents the carbon price on day t-1, and R_t represents the carbon returns.

Figure 3 shows the trend of returns. It can be noted that the sample is stationary, but simultaneously shows volatility clustering. Furthermore, all of the return series in the figure are subject to extreme volatility.

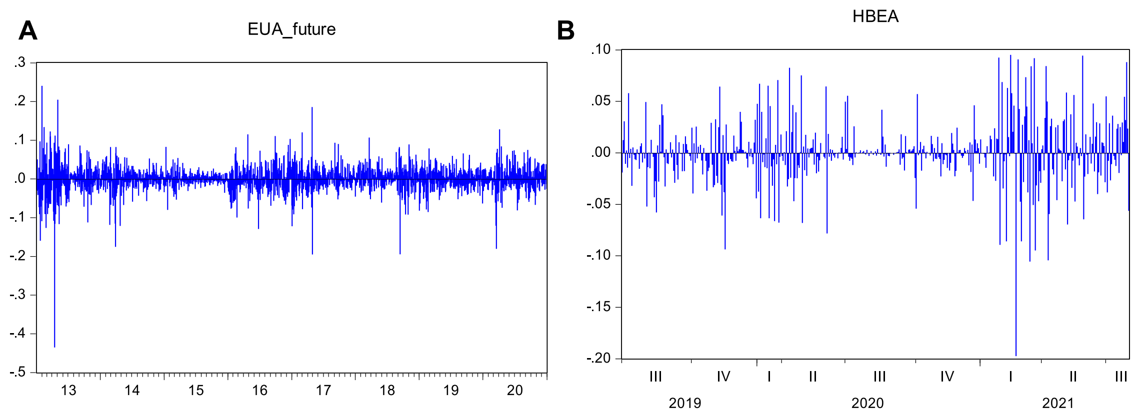

FIGURE 3
Carbon price yield trends. **(A)** EUA futures return trend; **(B)** Hubei spot price return trend. The sample period is from 1 January 2013, to 31 December 2020, for EUA futures and from 1 July 2019, to 30 July 2021, for Hubei spot returns.

TABLE 2 Data descriptive statistics. This table presents the descriptive statistics results of carbon price returns considered for the whole sample period. JB denotes the Jarque-Bera test statistic for the null of normality.

Variables	R_{EUA3}	R_{HBEA}
Mean	0.0008	0.0001
Median	0.0000	−0.0003
Maximum	0.2405	0.0952
Minimum	−0.4347	−0.1972
Std. Dev	0.0342	0.0306
Skewness	0.5423	−0.4601
Kurtosis	20.2870	8.1436
Jarque-Bera	26,073.8000	538.0974
Prob	0.0000	0.0000

4.2 Descriptive analysis

Table 2 shows the basic characteristics of EUA futures and Hubei spot returns. The minimum values of the two returns are −0.4347 and −0.1972. The maximum values of the EUA futures returns and Hubei spot returns are 0.2405 and 0.0952, respectively. Meanwhile, the mean value of the EUA futures returns is 0.0008 and the mean value of Hubei spot returns is 0.0001. The standard deviations of EUA futures returns and Hubei spot returns are 0.0342 and 0.0306, respectively. The kurtosis of all the return series exceeds three, and the skewness of these returns is not equal to zero. The skewness of the EUA futures return is greater than zero, indicating a right-skewed distribution. The skewness of the Hubei spot return is less than zero, indicating a left-skewed distribution. The two series have the same characteristics as other financial time series, with higher peaks and fatter tails.

The JB statistic shows that none of the return series follow a normal distribution. Figure 4 indicates that the quantile-quantile plot test results confirm this as well. Therefore, using the generalized error distribution (GED) to characterize the data in the modeling approach in this paper can more accurately explain the statistical features of the carbon return series.

4.3 Carbon price volatility characteristics

In this part, we examine the volatility characteristics of the series because the GARCH family model requires the series to be stable and to have conditional heteroskedasticity. Thus, before we establish the GARCH models, it is essential to test whether the two series are stationary and heteroskedastic.

4.3.1 Unit-root test

We examine whether the series is stationary by using the Augmented Dickey Fuller (ADF) test. Table 3 shows the results from the ADF test. The results for the EUA futures and Hubei spot return series all reject the null hypothesis, since the t-statistic values are equal to 0.0000, indicating that the two series are both stationary.

4.3.2 ARCH-LM test

We examine whether the series is heteroskedastic by using the ARCH-LM test. We regress the return series on the constant term to obtain the residual series and take the lags of order 1, order 5, and order 10 for the test. Table 4 shows the results of the ARCH effect test for the return series. Both the F-statistic and LM-statistic are significantly larger than the critical values, and the residuals of the return series have conditional heteroskedasticity. This means that the GARCH family of models can be used.

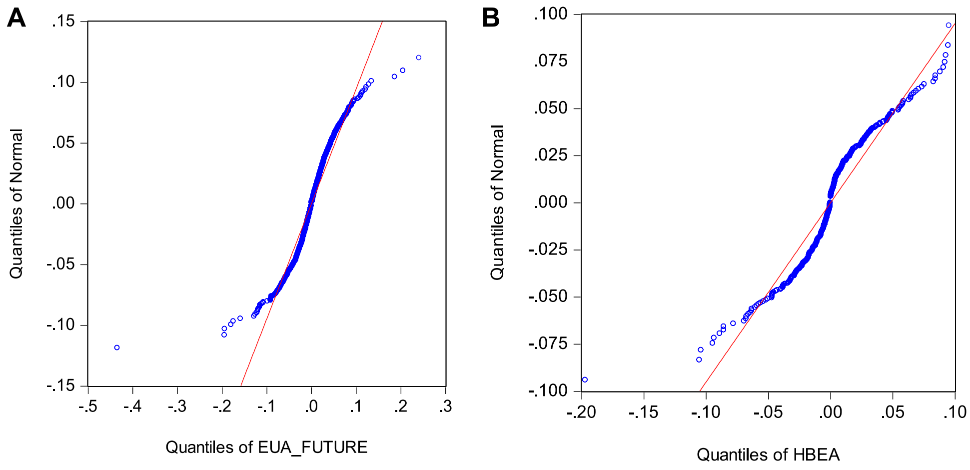

FIGURE 4
Quantile-quantile plots for returns. **(A)** EUA futures; **(B)** Hubei spot. The sample period is from January 1, 2013, to December 31, 2020, for EUA futures and from July 1, 2019, to July 30, 2021, for Hubei spot returns.

TABLE 3 ADF test of EUA futures and Hubei spot returns. The null hypothesis of the ADF test is the presence of a unit root, that is, the series is nonstationary.

	R_{EUA3}	R_{HBEA}
t-Statistic	−35.2274	−19.3779
Prob.*	0.0000	0.0000
Test critical values		
1%Level	−2.5661	−2.5699
5%Level	−1.9410	−1.9415
10%Level	−1.6166	−1.6162

4.4 Empirical results

In this part, we perform a modeling analysis of carbon price returns. First, we use the EGARCH model to evaluate the impact of positive and negative news on returns. Then, we use the modified ICSS algorithm to locate structural breaks in the returns and find the times when structural changes occur; then, we introduce them into the GARCH model as dummy variables to investigate the impact of event shocks on return volatility. In this paper, some of the structural breaks are generated at the time corresponding to the associated announcement in the news and are added to the model as dummy variables to investigate the impact of event shocks on return volatility. In further discussions, we compare data from phases II and III of EUA futures to see if there is continuity in the causes driving structural fractures.

4.4.1 Leverage effect analysis based on the EGARCH model

It is known that the volatility of financial assets tends to be asymmetric, which means that good news and bad news have different impacts on financial assets (Nelson, 1991). Therefore, this paper establishes an EGARCH model to study the leverage effect of the volatility of carbon return series. Table 5 shows the estimation results for the EUA futures. The fluctuations of EUA futures and Hubei spot returns are asymmetric, i.e., rises and falls in carbon price returns have different effects on future volatility.

TABLE 4 ARCH-LM test results. The null hypothesis is that a series of residuals exhibits no conditional heteroscedasticity. The *p*-value represents the significance of the corresponding test.

	Number of lags	F-statistic	Prob	Obs*R-squared	Prob
R_{EUA3}	1	27.9778	0.0000	27.6299	0.0000
	5	13.4695	0.0000	65.3989	0.0000
	10	7.1150	0.0000	69.1253	0.0000
R_{HBEA}	1	9.5616	0.0021	9.4109	0.0022
	5	9.9415	0.0000	45.4617	0.0000
	10	7.4020	0.0001	21.3779	0.0001

TABLE 5 Estimation results of the EGARCH (1, 1) model for EUA futures returns from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0740	0.0209	−3.5432	0.0004
Variance Equation				
α	−0.3501	0.0537	−6.5191	0.0000
β	0.2363	0.0260	9.0825	0.0000
γ	−0.0340	0.0166	−2.0462	0.0407
ω	0.9754	0.0063	155.8713	0.0000

TABLE 6 Estimation results of the EGARCH (1, 1) model for Hubei spot returns from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.2565	0.0433	−5.9280	0.0000
Variance Equation				
α	-0.9801	0.1045	−9.3756	0.0000
β	0.3803	0.0499	7.6175	0.0000
γ	0.0504	0.0349	1.4450	0.1485
ω	0.9015	0.0115	78.3068	0.0000

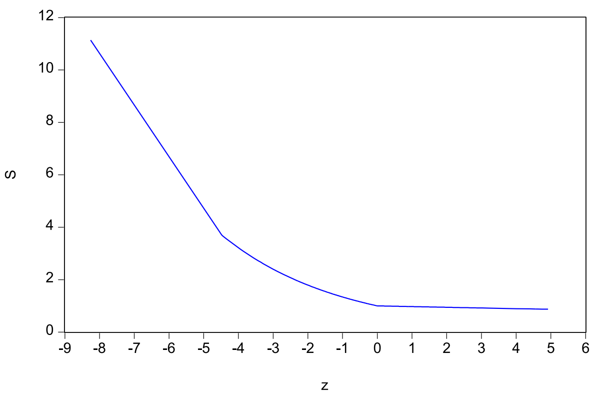

FIGURE 5
News impact curve of the EGARCH (1, 1) model of EUA futures returns.

TABLE 7 Structural breaks of EUA futures and Hubei spot returns.

	R_{EUA3}	R_{HBEA}
1	2013.05.14	2019.12.27
2	2014.02.24	2020.06.04
3	2014.05.21	2021.01.26
4	2015.06.02	2021.04.13
5	2015.12.10	
6	2016.11.10	
7	2017.04.28	
8	2020.03.11	

In addition, the coefficient of the asymmetric term γ is −0.0340, indicating that there is a leverage effect on the impact of carbon return volatility and that the impact of negative news on carbon market volatility is greater than that of positive news. Positive news generates a shock of a factor of 0.2023 ($\beta + \gamma$) to the volatility of EUA futures, and negative news generates a shock of a factor of 0.2703 ($\beta - \gamma$). The news impact curve for EUA futures returns is shown in Figure 5, which confirms the asymmetry of the impact.

Table 6 shows the estimation results for the Hubei spot returns. Although the coefficient γ of the asymmetric term of the Hubei spot returns is less than 0, the asymmetric term is not statistically significant, which means that there is no significant leverage effect. The reason is that China's carbon trading market is still at an early stage of development, and the main trading entities are enterprises whose emissions are controlled. In addition, China only has a spot trading market, which is less active than the EU market. After years of development and innovation, the EU-ETS has become more mature, with a broader investor structure and larger trade volume. Thus, compared to its traditional financial market, China's carbon market still needs to be developed.

4.4.2 Volatility analysis based on the modified ICSS-GARCH model

4.4.2.1 Structural break tests based on the modified ICSS algorithm

Using the modified ICSS algorithms presented in Section 2, we begin by detecting the structural breaks. We set the significance level for the algorithms at 0.05. Table 7 shows the results of structural break tests for the carbon market using the modified ICSS algorithm. There are nine structural change points in the EUA futures returns and four structural change points in the Hubei spot returns in the sample period. In this paper, some of the structural breaks are generated at the time corresponding to their announcement in the news and are added to the model as dummy variables. We find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market.

Table 8 shows the events that occurred on the dates corresponding to the structural breaks; the results indicate that the major event shocks caused the variance to change structurally. Next, we add the structural breaks as dummy

TABLE 8 Events corresponding to structural breaks.

	Date	Event
R_{EUA3}	2013.05.14	Shale oil production in the United States has expanded dramatically. The International Energy Agency (IEA) predicts that the United States will produce one-third of additional world crude oil supply during the next 5 years
	2014.02.24	The United Nations held a special event to highlight the importance of the needs of small island developing states in addressing climate change
	2015.06.02	Paris, France hosts the 26th World Gas Conference
	2015.12.10	The adoption of a new agreement on global climate change at the Paris Climate Change Conference will have an impact on the EU-ETS and EUA prices will fall in the future
	2016.11.10	The 22nd Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC), held in Morocco, focused on the key role of cities in the implementation of the Paris Agreement
	2017.04.28	The U.S. signs an executive order to expand offshore oil and gas drilling
	2020.03.11	The World Health Organization (WHO) declares the novel coronavirus (COVID-19) outbreak a global pandemic. Oil prices continue to be affected by global uncertainties
	2020.04.22	COVID-19 pandemic stalls global economic recovery. The combination of falling demand, rising supply caused such a pronounced crude petroleum price plunge
R_{HBEA}	2019.12.27	The UN Climate Change Conference COP 25 took place under the Presidency of the Government of Chile
	2020.06.04	Price changes due to approaching performance period
	2021.01.26	China stated it will further strengthen domestic efforts to adapt to climate change and comprehensively improve climate risk resilience at the Climate Adaptation Summit

TABLE 9 Parameter estimates of the AR (1)—GARCH (1, 1) model for EUA futures returns in phase III, without structural breaks from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0703	0.0213	−3.3053	0.0009
Variance Equation				
α	0.1190	0.0161	7.3805	0.0000
β	0.8743	0.0155	56.501	0.0000

TABLE 10 Parameter estimates of the MA (1)—GARCH (1, 1) model for Hubei spot returns without structural breaks from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
MA (1)	−0.2862	0.0397	−7.2178	0.0000
Variance Equation				
α	0.2436	0.0367	6.6409	0.0000
β	0.7403	0.0250	29.6049	0.0000

variables to the GARCH model to compare how important events affect the volatility of carbon prices.

4.4.2.2 Analysis of the GARCH model based on structural breaks

Using the modified ICSS algorithm, we have found structural breaks. Then we introduce them into the GARCH model for comparative analysis. We compare two models: one without structural change points and the other with structural change points, which are given individually in both cases.

4.4.2.2.1 GARCH model without structural breaks. First, we use the GARCH model without structural breaks. Tables 9, 10 show the estimation results of the GARCH model. For EUA futures and Hubei spot returns, all parameters are significant. The coefficients of α and β in the model are positive, and their sum is close to 1, indicating that the volatility of the carbon market has persistence and long memory.

TABLE 11 Parameter estimates of the AR (1)—GARCH (1, 1) model for EUA futures returns in phase III, with structural breaks from 1 January 2013, to 31 December 2020.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
AR (1)	−0.0679	0.0216	−3.1376	0.0017
Variance Equation				
α	0.1175	0.0165	7.1255	0.0000
β	0.8695	0.0156	55.8617	0.0000
Dummy	0.0006	0.0002	3.3950	0.0007

4.4.2.2.2 GARCH model with structural breaks. We adopt the modified ICSS-GARCH model to further analyze the volatility characteristics of the carbon market. Tables 11, 12 illustrate the results of the estimation. We find that the characteristics of volatility are attenuated when we consider structural breaks. We observe a decrease in the sum of α and

TABLE 12 Parameter estimates for the MA (1)—GARCH (1, 1) model for Hubei spot returns with structural breaks from 1 July 2019, to 30 July 2021.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Mean Equation				
MA (1)	−0.2796	0.0409	−6.8393	0.0000
Variance Equation				
α	0.1745	0.0273	6.3987	0.0000
β	0.7985	0.0212	37.734	0.0000
dummy	0.0013	0.0005	2.5024	0.0123

β for both EUA futures and Hubei spot returns. The sum of α and β for EUA futures returns decreases from 0.9933 to 0.9870, and the sum of α and β for Hubei spot returns decreases from 0.9838 to 0.9730. This indicates that the strong persistence and long memory characteristics of volatility become weaker after we add the structural breaks as a dummy variable to the model. The modified ICSS-GARCH model reduces the pseudovolatility of the return series and enhances the model's accuracy (Malik et al., 2005).

Table 13 depicts the results of the ARCH-LM test for the residuals after we model the return series. The p-value of the residual series is greater than 0.05 for lag orders of 1, 5 and 10, and therefore the null hypothesis is accepted. This shows that after modeling, the conditional heteroskedasticity in the series is removed, which means that the model fits well.

5 Further discussion

5.1 Analysis of EU-ETS phase II

We replace our dataset with the EU-ETS phase II trading data for further discussion of the volatility of EUA futures' returns. Due to data availability, the scope for the prices of EUA futures' returns is from 2 January 2008, to 31 December 2012. Table 14 illustrates the basic characteristics of EUA futures returns in phase II. The descriptive statistics show that the mean value of the return in phase II is -0.0010, which is lower than the value of 0.0008 in phase III, indicating that the return of EUA futures is gradually increasing. The standard deviation of phase II is 0.0271, which is not significantly different from phase III, and the price fluctuation is more stable. In addition, the returns of both phases have the characteristics of higher peaks and fatter tails and do not follow a normal distribution.

We also conducted ADF and ARCH-LM tests on the data of EUA futures in phase II, and the results show that the returns remain stationary and the residuals of the return series are conditionally heteroskedastic. Next, we analyze the volatility of EUA futures returns in phase II using the same methods as in Section 3.

The estimation results for the EGARCH (1, 1) model are shown in Table 15. The fluctuations in phase II of the EUA futures are asymmetric. The coefficient of the asymmetric term γ is −0.0674, indicating that there is a leverage effect on the impact of carbon return volatility and that the impact of negative news on carbon market volatility is greater than that of positive news. Positive news generates a shock of a factor of 0.1475 ($\beta + \gamma$) to volatility, and negative news generates a shock of a factor of 0.2823 ($\beta - \gamma$).

We examine the structural break points uncovered by using the modified ICSS algorithms. There are four structural breaks in the EUA futures returns in phase II: they occurred on 21 October 2008; 16 June 2009; 28 May 2010; and 22 June 2011. We also add these structural breaks to the model as dummy variables. Table 16 illustrates the estimation results of the GARCH (1, 1) model without the structural breaks. Table 17 shows the results of the ICSS-GARCH (1, 1) model with structural breaks. The findings show that the characteristics of volatility are attenuated once we consider structural breaks. There is a decrease in the sum of α and β for both phases. The sum of α and β for EUA futures returns decreases from 0.9936 to 0.9847.

This is consistent with the findings for phase III, in which EU-ETS volatility does not change significantly between the two phases, confirming that phase II volatility characteristics persist into phase III. This also indicates that the strong persistence and long memory characteristics of volatility become weaker after we add the structural breaks as dummy variables to the model. The

TABLE 13 ARCH-LM test results for residual series. The null hypothesis is that a series of residuals exhibits no conditional heteroscedasticity. The p-value represents the significance of the corresponding test.

	Number of lags	F-statistic	Prob	Obs*R-squared	Prob
R_{EUA3}	1	0.0626	0.8025	0.0626	0.8024
	5	0.3687	0.8703	1.8471	0.8699
	10	0.5542	0.8519	5.5569	0.8510
R_{HBEA}	1	0.9329	0.3346	0.9350	0.3336
	5	0.5851	0.7114	2.9448	0.7085
	10	0.6466	0.7738	6.5295	0.7690

TABLE 14 Phase II data descriptive statistics. This table presents the descriptive statistics results of carbon price returns considered for the whole sample period. JB denotes the Jarque-Bera test statistic for the null of normality.

Variables	Mean	Std. Dev	Skewness	Kurtosis	Jarque-bera	Prob
R_{EUA2}	−0.0010	0.0271	0.0837	6.9123	819.7549	0.0000

TABLE 15 Estimation results of the EGARCH (1, 1) model of EUA futures returns in phase II from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	−0.3826	0.0744	−5.1423	0.0000
β	0.2149	0.0340	6.3273	0.0000
γ	−0.0674	0.0170	−3.9598	0.0001
ω	0.9709	0.0080	120.7018	0.0000

TABLE 16 Parameter estimates of the GARCH (1, 1) model for EUA futures returns in phase II without structural breaks from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	0.1008	0.0167	6.0045	0.0000
β	0.8928	0.0170	52.5048	0.0000

TABLE 17 Parameter estimates of the GARCH (1, 1) model for EUA futures returns in phase II with structural breaks from 2 January 2008, to 31 December 2012.

Variable	Coefficient	Std. Error	z-Statistic	Prob
Variance Equation				
α	0.0947	0.0170	5.5775	0.0000
β	0.8970	0.0172	52.223	0.0000
dummy	0.0005	0.0002	2.2230	0.0262

modified ICSS-GARCH model reduces the pseudovolatility of the return series and enhances the model's accuracy. A proper assessment of short-term price and volatility is a critical issue in the carbon market since effectively measuring volatility risk is critical for carbon market managers in a complex market.

To summarize, our study shows the following findings: First, there is a leverage effect on the impact of carbon return volatility, and the impact of negative news on carbon market volatility is greater than that of positive news. This is consistent with previous research demonstrating that the returns on financial assets are leveraged and that positive and negative news have different impacts on return volatility (Paolella and Taschini, 2008; Dutta, 2018). Secondly, we find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market. Wang et al. (2019) demonstrated that all externalities of the carbon market, whether energy prices or policy announcements, are reflected in trading behavior and impact the demand and supply of carbon permits *via* trading, which influences carbon pricing. We extend this conclusion. Finally, our results are consistent with previous results using the modified ICSS-GARCH model to study financial market data (Malik et al., 2005; Wen et al., 2020). The results show that the modified ICSS-GARCH model is also applicable to the study of carbon market volatility and that the model can reduce the pseudovolatility of the return series to a certain extent and improve the accuracy of the model.

5.2 Policy recommendations

The findings of this study are potentially significant for further research into carbon emission permits. They help policymakers and investors in the carbon market identify risks and develop strategies to minimize them.

Firstly, regulators should enhance carbon price monitoring and focus on short-term shocks in the carbon market to reduce trading risks. Studies have shown that when the carbon market is subject to exogenous shocks, prices are prone to dramatic fluctuations and the market does not compensate for potential risks. Market managers should recognize and identify abnormal price fluctuations and forecast the trend. In addition, market management should establish stability reserves in order to minimize extreme price changes in response to exogenous shocks, reduce trade risks, and improve market stability.

Second, the Chinese carbon market should improve the system design. The findings indicate that the EU-ETS price is less volatile and more stable than the carbon market in China. In the short term, the Chinese carbon market is inactive, participants are risk-averse, and products lack diversity. In the long term, the Chinese carbon market needs a comprehensive development plan and a well-structured market framework. It still needs to be improved in many ways, and the design of the system should be strengthened.

Finally, the Chinese market should boost the development of carbon finance instruments. Chinese carbon credits can only be traded on the spot market. To increase the liquidity of the carbon market, policymakers should encourage the development of derivative products such as carbon futures, which can diversify investment portfolios and attract more investors to participate in trading. Stability in the carbon market can be established through the use of derivatives for price discovery and risk aversion. Prior studies suggest that the EU-ETS reduces the volatility of spot prices after the introduction of futures products, and spreads the uncertainty of spot prices through a hedging mechanism (Chevallier et al., 2011). Furthermore, derivatives can be used for price discovery and risk aversion in order to stabilize the carbon market. It can also increase market activity and encourage both institutional and individual investors to trade actively in the carbon market.

6 Conclusion

Responding to climate change, realizing carbon emission reductions at the lowest cost by economic market means and reversing the increasing trend of greenhouse gas emissions are major challenges for the world.

In this paper, we investigate the volatility characteristics of the EU-ETS and the Chinese Hubei carbon market, by using the modified ICSS-GARCH model. The study shows the following findings. 1) There is a leverage effect on the impact of carbon return volatility, and the impact of negative news on carbon market volatility is greater than that of positive news. The leverage effect in the Hubei carbon market was not statistically significant during the sample period. We surmise that this result could be due to inactive market trading and trading entity limits. 2) We find that the international climate and energy conferences, abnormal changes in prices of traditional energy such as oil, and global public health emergencies all affect the volatility of the carbon market and cause certain shocks to the carbon trading market. 3) We adopt the modified ICSS algorithm to find the structural breaks and introduce them as dummy variables to investigate the impact of event shocks on the volatility of the carbon market. The results indicate that the ICSS-GARCH model can reduces the pseudovolatility of the return series to a certain extent and improve the accuracy of the model. In addition, our results hold after we replace the data from EUA futures phase III with those from phase II, indicating that our model is robust and that the factors affecting phase II persist into phase III.

Our findings could be important for carbon emission permit research. They help policymakers and investors identify risks and develop prevention measures. Regulators can minimize trade risks by enhancing monitoring of carbon prices. Policymakers should improve the way the system is set up and speed up the development of carbon finance instruments for the Chinese carbon market.

Data availability statement

The CSV data used to support the findings of this research are available from the corresponding author upon request.

Author contributions

HY: conceptualization, software, data curation, and writing original draft; HW: methodology, reviewing, and editing; CL: software, data curation, and writing original draft; ZL: methodology, reviewing, and editing; SW: conceptualization, supervision, and funding acquisition.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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