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Zhen-Hua Feng
Le-Le Zou
Yi-Ming Wei

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Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street, Haidian District
Beijing 100081
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Yi-Ming Wei
Director of Center for Energy and Environmental Policy Research, Beijing Institute of Technology

For more information, please contact the office:

Address:
Director of Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street
Haidian District, Beijing 100081, P.R. China

Access:
Tel: +86-10-6891-8551
Fax: +86-10-6891-8651
Email: ceeper@vip.163.com
Website: http://ceep.bit.edu.cn/english/index.htm

Carbon price volatility：Evidence from EU ETS

Zhen-Hua Feng [a, b, d], Le-Le Zou [b, d], Yi-Ming Wei [b, c] *

[a] School of Management, University of Science and Technology of China, Hefei, 230026, China;
[b] Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing, 100081, China;
[c] School of Management and Economics, Beijing Institute of Technology, Beijing, 100081, China;
[d] Institute of Policy and Management, Chinese Academy of Science, Beijing, 100190, China;

Abstract: This paper examines carbon price volatility using data from the European Union Emission Trading Scheme from a nonlinear dynamics point of view. First, we use a random walk model, including serial correlation and variance ratio tests, to determine whether carbon price history information is fully reflected in current carbon price. The empirical research results show that carbon price is not a random walk: the price history information is not fully reflected in current carbon price. Second, use R/S, modified R/S and ARFIMA to analyze the memory of carbon price history. For the period April 2005 to December 2008, the modified Hurst index of the carbon price is 0.4859 and the d value of ARFIMA is -0.1191, indicating short-term memory of the carbon price. Third, we use chaos theory to analyze the influence of the carbon market internal mechanism on carbon price, i.e., the market's positive and negative feedback mechanism and the heterogeneous environment. Chaos theory proves that the correlation dimension of carbon price increases. The maximal Lyapunov exponent is positive and large. There is no obvious complex endogenous phenomenon of nonlinear dynamics the carbon price fluctuation. The carbon market is mildly chaotic, showing both market and fractal market characteristics. Price fluctuation is not only influenced by the internal market mechanism, but is also impacted by the heterogeneous environment. Finally, we provide suggestions for regulation and development of carbon market.

Key words: carbon price; EU ETS; nonlinear dynamics; feedback mechanism; heterogeneous environment

1 Introduction

A lot of attention is being paid to climate change because of greenhouse gases, which are regulated by

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* Corresponding author:

Y.-M. Wei; E-mail: ymwei@deas.harvard.edu, wei@bit.edu.cn ; Tel./ Fax: +86-10-68918651

the United Nations Framework Convention on Climate Change among the contracting states. Several methods have been used to control carbon dioxide emissions. Carbon tax is one of the usually ways [1, 2]. Other policy and new technology are also been used [3, 4]. With greenhouse gas emissions having become a scarce resource, the international greenhouse gas emissions trading market (carbon market) has developed rapidly. For example, the trading volume under the European Union Emissions Trading Scheme (EU ETS) grew from 8.49 million tons in 2004 to 3093 million tons in 2008, with trading worth US$8.2 billion in 2005 and US$919.10 billion in 2008[5, 6].

The carbon market has some common attributes of markets, but also has its own peculiar characteristics. Price volatility is one such attribute. Carbon price fluctuation plays a significant role in the carbon market and carbon dioxide emissions reduction. The carbon market is from general trading markets, as international politics and negotiations leads to great volatility and complex changes in the carbon price. 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 until the European Commission issued a formal certification data on May 15th, 2006, after which prices returned to normal (*May incident*). At the same time, a clustering effect and information shock asymmetry have appeared in carbon price fluctuation. Therefore, the general linear methods of market research can not fully explain the inherent features.

Research on carbon price has focused on the relationship between carbon price and other energy prices [7]. For example, Alberola et al. [8] established a model of carbon price, energy prices and weather to analyze carbon price changes and the impact of structural break points from 2005 to 2007 in EU ETS. The results illustrated that the carbon price was not only influenced by energy prices and forecast error, but also by unanticipated weather temperature. Chevallier [9] used a generalized auto regressive conditional heteroscedasticity (GARCH) model to explain the relationship between EU ETS carbon futures and macroeconomic factors. He used GARCH (p, q), ARCH and TGARCH models to analyze the change of the carbon futures return rate under macroeconomic conditions. Analysis has shown that the EU emissions allowances (EUAs), as a new type of commodity, are obviously influenced by electricity demand. Oberndorfer [10] researched the effects of the power companies' stock prices in EU ETS. The results illustrated that the dynamic performance of carbon price was very important to electric power enterprises: the carbon stock price had a positive correlation with power, although this effect was not asymmetric, and the carbon market effect was obviously different according to time and country. Milunovich [11] used an error correction model, cointegration and a Granger causality test to analyze market efficiency and carbon futures price discovery in the EU. The results show that spot prices and futures markets share information efficiently and contribute to price discovery jointly. Benz and Truck [12] established Markov switching and AR-GARCH models to study the returns of emission allowances. Wei et al. [13] studied the relationship between carbon price and energy prices including power, oil, coal and natural gas.

In our opinion, the carbon market is a complex volatility model, the volatility of carbon price being affected by energy prices and weather, and also by the development of the carbon market and traders' behavior. Therefore, research only focused on the relationship between carbon and energy prices is insufficient. In this paper, we introduce a nonlinear dynamic method to analyze carbon price fluctuation.

The rest of the paper is organized as follows: Section 2 reviews the methodologies applied in the paper. Section 3 describes the source data in the paper. The empirical results and discussion are presented in Section 4. Section 5 analyses the hypothesis of volatility. Conclusions and policy suggestions are offered in Section 6.

2 Methodologies

In this paper, we (1) use a random walk model to investigate whether carbon price history is fully reflected in current carbon price; (2) use classic R/S analysis, modified R/S analysis, and an autoregressive fractionally-integrated moving-average (ARFIMA) model to study the influence of current carbon price on future price movements; and (3) use chaos theory to analyze the influence of the internal market mechanism on the carbon price.

2.1 Random walk model

Is carbon price history information fully reflected in current carbon price? Is carbon price fluctuation a random walk? The basic condition of a weak-form efficient market is that the carbon price is a random walk, which means that carbon price fluctuations meet independent and identically distributed (IID) increments.

The model is: $\log P_t = \mu + \log P_{t-1} + \varepsilon_t$, where ε_t is independently and identically distributed (random walk hypothesis 1 [RW1]), $\mu = E(R_t)$ is the expected price change or drift and $p_t = \log P_t$ is the log of the carbon price. Independence not only implies that increments are uncorrelated, but that any nonlinear functions of the increments are uncorrelated. According to relaxing the distributional assumption of Campbell et al. [14], ε_t is independent but not identically distributed. We, therefore, relax the independence assumption of RW2 to include processes with dependent but uncorrelated increments (RW3).

In this paper, we apply the serial correlation to test RW1 of carbon price. Lo and MacKinlay [15] proposed the variance ratio, and further confirmed that for both homoscedasticity and heteroscedasticity, the variance ratio test is more reliable than the serial correlation test [16]. The serial correlation test and the unit root test assume that carbon price contracts are normally distributed variables. However, the variance ratio test does not require this assumption.

The principle of the variance ratio test is as follows: If carbon price are a random walk process, then the variance of period K should be k-fold the sample period. In this paper, we build variance ratio statistics for analysis according to whether the carbon price is homoscedastic (RW1) or heteroscedastic (RW3).

If the results of RW1and RW3 in the variance ratio test are different, carbon price may have heteroscedasticity, ARCH-LM can be used to test whether the time series have heteroscedasticity.

2.2 R/S analysis

R/S analysis was originally proposed by Hurst [17], and further developed by Mandelbrot and Wallis [18] and Mandelbrot [19, 20].

Consider a times series of carbon price returns $\{x_t\}$ for integer n, k $(k \le n \le t)$, $x_t = \log P_t - \log P_{t-1}$, the range deviation of the carbon price is $R(n) = \max_{1\le k\le n} \sum_{j=1}^{k}(x_j - \overline{x_n}) - \min_{1\le k\le n} \sum_{j=1}^{k}(x_j - \overline{x_n})$ and the standard deviation is $S(n) = \sqrt{\frac{1}{n}\sum_{j=1}^{k}(x_j - \overline{x_n})^2}$. The Q statistic is defined as: $Q_n = \frac{R(n)}{S(n)}$, $Q_n = cn^H$ when $n \to \infty$, c is constant.

H is the Hurst index of carbon. If 0<H<0.5, the carbon price represents short-term memory. Anti-persistence means that if the signal is up (down) in the last period then it tend to go down(up) in the next period. If H=0.5, the carbon price is determined to be random. If 0.5<H<1, the carbon price represents long-term memory, persistence.

According to Lo [21] and Chueng and Lai [22]'s studies, if the carbon price series exhibits short-term memory and heterogeneity features such as non-stationarity, the Hurst index of classical R/S would be biased, meaning the results would always be long-term memory even if the time series has strong short-term indication. Moreover, the volatility of the carbon price is more rapid, possibly because of short-term memory, i.e., non-stationarity. Therefore, we use modified R/S analysis as follows.

The Q statistic is defined as:

$$Q_n = \frac{R(n)}{\sigma_n(q)}, \sigma_n^2(q) = \frac{1}{n}\sum_{j=1}^{n}(x_j - \bar{x})^2 + \frac{2}{n}\sum_{j=1}^{q}\omega_j(q)\{\sum_{i=j+1}^{n}(x_{i-j} - \bar{x})(x_j - \bar{x})\}$$

$\sigma_n^2 x + 2\sum_{j=1}^{q}\omega_j(q)\rho$, $\omega_j(q) = 1 - \frac{j}{q+1}$, q<n， $\sigma^2 x = s^2$, ρ is autocovariance of X and q is lag.

2.3 ARFIMA model

ARFIMA model distribution is not dependent on specific assumptions. ARFIMA is a more reliable test of carbon price memory.

The ARFIMA (p, d, q) model of carbon price returns is as follows:

$\Phi_p(B)(1-B)^d x_t = \Theta_q(B)\varepsilon_t$， where p and q are both integers.

$\Phi_p(B) = 1 - \Phi_1 B - \cdots - \Phi_p B_p$， carbon price autoregressive operator with lag p.

$\Theta_q(B) = 1 + \Theta_1 B + \cdots + \Theta_q B^q$， carbon price moving average operator with lag q

$(1-B)^d = 1 - dB - \frac{d(1-d)}{2!}B^2 - \cdots$， the fractal dimension for the differential operator。ε_t is IID, the mean is 0 and the variance is σ_ε^2. When d=0，ARFIMA changes to ARIMA，and carbon price show short-term memory. When $d \neq 0$ and $d \in (-0.5, 0.5)$， carbon price show long-term memory.

2.4 Chaos

A dynamic system is described by independent state variables, called “phase space”. We assign the carbon market as a dynamic system. However, there are few observations of the carbon market, mostly only for carbon price. Therefore, using carbon price, we select a delay time and suitable embedded dimension to establish the multi-dimensional phase space.

It is difficult to know the system dynamic equations of the carbon market. We calculate some eigenvalues of carbon price to partly understand the system movement. The following two eigenvalues will be used to judge whether or not the carbon market is in a chaotic state:

First, the phase space attractors of the system have fractal dimension. We use Grassberger and Procaccia [23] to calculate the correlation dimension of carbon price to measure the system space complexity, to judge whether the system is in a chaotic state.

Consider the times series $X = \{x_1, x_2, x_3, ..., x_N\}$, $\{x_t\}$ is carbon price returns, m is the embedded dimension, $C_m(r) = \frac{1}{N^2}\sum_{i,j=1}^{N}\theta(r - |X_i - X_j|)$ is correlation integral, $\theta(x)$ is the Heaviside function[1].

[1] See Grassberger and Procaccia [23] for an extensive discussion on this topic

The correlation dimension is $D = \lim_{r \to 0} \frac{\log C_m(r)}{\log r}$

Second, we use Wolf [24] to calculate the maximal Lyapunov exponent of carbon price to judge the sensitivity of the system's initial conditions.

Let τ is the time delay, reconstitute state space: $Y(t_i) = (x(t_i), x(t_i+\tau), \cdots, x(t_i+(m-1)\tau)), (i = 1, 2, \cdots, \mathrm{N})$,

$L_0' = |Y(t_1) - Y_0(t_1)| > \varepsilon$, $L_1 = |Y(t_1) - Y_1(t_1)| < \varepsilon$, $\lambda = \frac{1}{t_M - t_0} \sum_{t=0}^{M} \log_2(\frac{L_i'}{L_i})$ is the maximal Lyapunov exponent. M is the total number of replacement steps[2].

3 Data source

The data for this study were selected from the European Climate Exchange (ECX). The EU ETS is divided into two phases: (1) from 2005 to 2007; and (2) 2008 to 2012. Therefore, several major ECX carbon futures contracts had to be selected for the study as the contract prices of the different phases show larger differences while those of the same phase are similar. We use the data selected from the following periods: April 2005 to December 2006 (Dec06); April 2005 to December 2007 (Dec07); April 2005 to December 2008 (Dec08); and April 2005 to February 2009 (Dec09). The carbon price trend is shown in Figure 1.

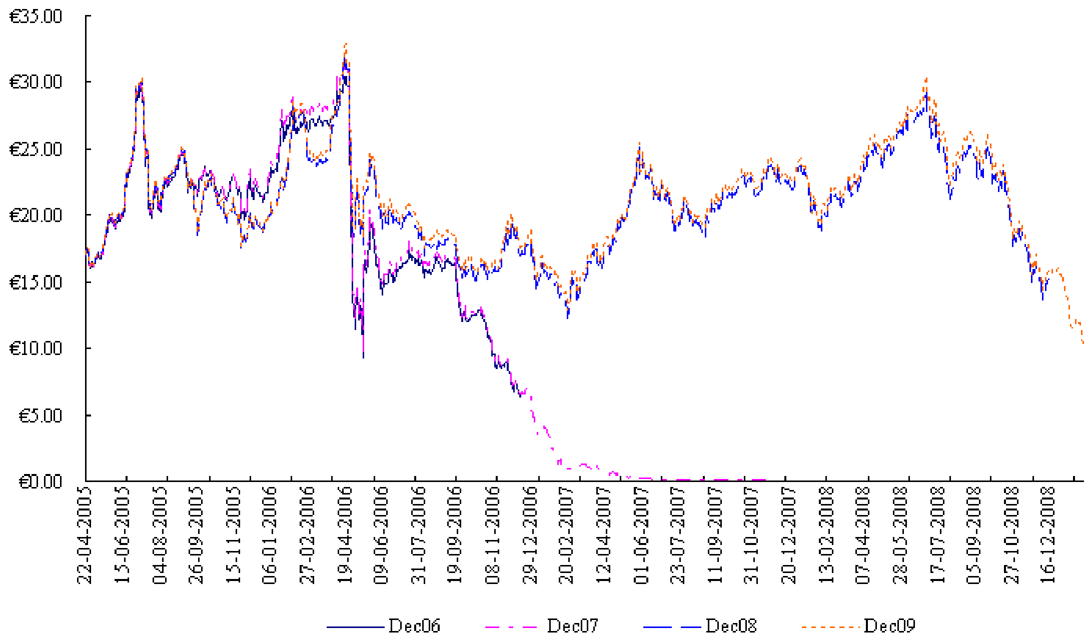

Fig. 1. Carbon price of the European Climate Exchange for April 2005 to February 2009

[2] See Wolf [24] for an extensive discussion on this topic

4 Results and discussion

4.1 Is carbon price history information fully reflected in current carbon price?

The unit root test of carbon price series shows the first different are stationary and the time series are all I (1) (Table 1), which is the essential condition for a random walk. The results of the serial correlation and variance ratio test are shown in Tables 2 and 3, respectively.

Table 1

Results of unit root test

Futures	Level	1st difference	Results
Dec06	-0.9191	-6.8180***	I(1)
Dec07	0.0894	-4.9775***	I(1)
Dec08	-0.3043	-8.6838***	I(1)
Dec09	-0.6054	-9.4371***	I(1)

Note: the lag length based on Akaike information criterion, *** denotes significance levels at 1 percent.

Table 2

Results of serial correlation test

Futures	Q(q)	Q-value	P-value	Futures	Q(q)	Q-value	P-value
Dec06	Q(1)	0.033	0.856	Dec07	Q(1)	0.142	0.706
	Q(2)	3.083	0.214		Q(2)	8.382	0.015
	Q(3)	8.811	0.032		Q(3)	9.909	0.019
	Q(4)	15.543	0.004		Q(4)	10.102	0.039
	Q(5)	16.094	0.007		Q(5)	10.170	0.071
Dec08	Q(1)	0.000	0.989	Dec09	Q(1)	0.008	0.929
	Q(2)	0.145	0.930		Q(2)	1.031	0.597
	Q(3)	0.369	0.947		Q(3)	1.305	0.728
	Q(4)	1.478	0.831		Q(4)	2.399	0.663
	Q(5)	1.480	0.915		Q(5)	2.487	0.779

Table 3

Results of variance ratio test

Futures	q	VR（q）	$\psi(q)$	$\psi^*(q)$
Dec06	2	1.1140	2.3464**	0.5769
	4	1.1809	1.9906**	0.5747
	8	1.3873	2.6959*	0.9549
	16	1.3721	1.7406	0.7080
Dec07	2	0.8207	-4.6792*	-0.8118
	4	0.6632	-4.6986*	-0.9875
	8	0.6255	-3.3042*	-0.9178
	16	0.6411	-2.1280**	-0.7473
Dec08	2	1.1222	3.7378*	2.7265*
	4	1.2250	3.6769*	2.4849**
	8	1.2781	2.8743*	1.9215

	16	1.2472	1.7173	1.1424
Dec09	2	1.1207	3.7586*	2.7820*
	4	1.2414	4.0181*	2.7137*
	8	1.3087	3.2498*	2.1675**
	16	1.3056	2.1623**	1.4362

Note: $\psi(q)$ and $\psi^*(q)$, respectively, are the variances of the homoscedastic and heteroscedasticity-adjusted statistics, subject to a mean of 0 and standard deviation of normal distribution of 1. The 5% and 1% significant threshold levels were 1.96 and 2.58, respectively. If the calculated statistic is greater than the critical value, then it means that the null hypothesis (VR (q) = 1) is rejected. The asterisks * and ** denote significance levels at 1 and 5 percent, respectively.

Table 4

Results of ARCH-LM test

Futures	F-statistic	P-value	LM-statistic	P-value
Dec06	50.3143	0.0000	45.1457	0.0000
Dec07	139.8863	0.0000	116.2742	0.0000
Dec08	1.9350	0.1645	1.9351	0.1642
Dec09	2.0946	0.1481	2.0944	0.1478

Random walk of the carbon price is not obvious. The carbon market is not weak-form efficient markets and the history information of prices is not fully reflected in current carbon price, suggesting non-linearity.

From Table 2, Dec06 is a mild random walk which shows features of a weak-form efficient market. Dec07 is not a random walk, but Dec08 and Dec09 are random walks. Dec06 supports the null hypothesis (RW1) at the 95% level and is a random walk, but Dec07 is not a random walk under the same circumstances (Table 3). Dec06 and Dec07 support the null hypothesis (RW3) with heteroscedasticity adjustment, being a random walk. Dec08 and Dec09 show a mild random walk but do not support the null hypothesis after heteroscedasticity adjustment. At the same time, some of the carbon price such as Dec06 and Dec 07 show serious heteroscedasticity (Table 4).

4.2 Influence of carbon price history on future carbon price trends

Does carbon price history have any influence on the future trend of carbon price? If so, is this impact short-term or long-term? We use R/S, modified R/S and ARFIMA to analyze the long-term memory of history carbon price.

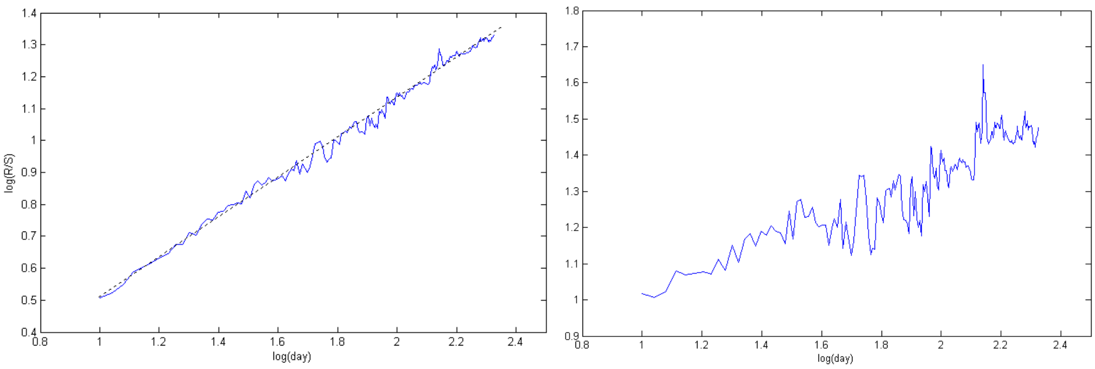

Fig. 2. R/S analysis of Dec06 returns **Fig. 3.** V statistics of Dec06 returns

Table 5

R/S analysis of carbon price on the European Climate Exchange

		Dec06	Dec07	Dec08	Dec09
R/S	H	0.6254	0.6097	0.5396	0.5441
analysis	V	1.2390	1.4441	1.0764	1.2155
		[<0.40]	[<0.20]	[<0.80]	[<0.50]
Modified	ρ	0.1095	-0.1249	0.1213	0.1195
R/S	q	4	6	5	5
analysis	H	0.5447	0.5181	0.4859	0.4931
	V(q)	1.1002	1.6103	0.9512	1.0608
		[<0.70]	[<0.10]	[<0.90]	[<0.70]

Note: ρ is the serial autocorrelation coefficient with lag 1 of carbon price. q is in accordance with Andrews [25] and Lo [21]. The V statistic is in accordance with Lo [21]. P-values are given into brackets.

Classical R/S analysis shows that short-term memory is more obvious than long-term memory. Moreover, the carbon market exhibits a fractal structure, indicating carbon price memory is unstable (Table 5). The Hurst index of carbon price is greater than 0.5, but the V statistics refute that carbon price have long-term memory. Fractal dimension D (2-H) smaller than 1.5, which is the fractal dimension of Brownian motion. The closer the H index is to 0.5, the more obvious the random process is. Dec08 and Dec09 exhibit more random and “market-oriented” behavior than Dec06 and Dec07. The carbon price cycle is unstable because the peak value of the V statistics is unstable for Dec06 (Fig. 3). Modified R/S analysis also supports these findings.

The difference in the results of classic R/S and modified R/S analysis may be because of the following reasons: The data we used are day prices with lots of noise, and, therefore, may have short Markov dependence [26]. Moreover, different from general trading markets, international politics, negotiations and temperature lead to great volatility of carbon price, making short-term memory more obvious.

Table 6

ARFIMA analysis of carbon price on the European Climate Exchange

	Dec06	Dec07	Dec08	Dec09
d	-0.2809	-0.0642	-0.1191	0.0010
t	-1.6621***	-0.5612	-0.9031	0.0089

Note: ***is significant at the 10% level. The d and t are calculated in accordance with Geweke and Porter-Hudak [27].

Table 7

Volatility of Dec 08 analysis

	R/S’H	V	ρ	q	Modified R/S’H	V(q)	d	t
r_t	0.5396	1.0764 [<0.90]	0.1213	5	0.4859	0.9512 [<0.90]	-0.1191	-0.9031

$\left\|r_t - \bar{r}\right\|$	0.7426	2.1002 [<0.005]	0.1462	5	0.6488	0.8238 [<0.975]	0.2153	1.6736***
$(r_t - \bar{r})^2$	0.7102	1.6949 [<0.10]	0.0525	3	0.6582	1.4076 [<0.30]	0.0748	0.6316

Note: ρ is the serial autocorrelation coefficient with lag 1 of the carbon price. q is in accordance with Andrews [25] and Lo [21]. The V statistic is in accordance with Lo [21]. The d and t are calculated in accordance with Geweke and Porter-Hudak [27]. P-values are given into brackets.

The result of ARFIMA analysis is the same as R/S and modified R/S except for Dec06 which has mild long-term memory (Table 6). Table 7 shows that the Hurst index of mean absolute return deviation is large. The ARFIMA model also shows strong long-term memory of carbon price. The mean square deviation shows a strong long-term memory through both R/S analysis and modified R/S analysis, but the ARFIMA model and does not support this hypothesis.

Therefore, analysis of the influence of carbon price history on the future trend of carbon price is short-term.

4.3 Influence of the internal mechanism of the carbon market on carbon price volatility

The carbon market is similar in character to commodity markets, but also has its own peculiarities. The carbon market is similar to financial markets in that price volatility is essentially caused by internal instability rather than external instability. However, the external environment, such as policies, negotiations, allowances etc., causes great temporary price fluctuations, restore to equilibrium on their own. We use chaos theory to analyze how the carbon market mechanism impacts carbon price volatility.

We embedded the carbon price in two-dimensional and three-dimensional space by phase-space reconstruction.

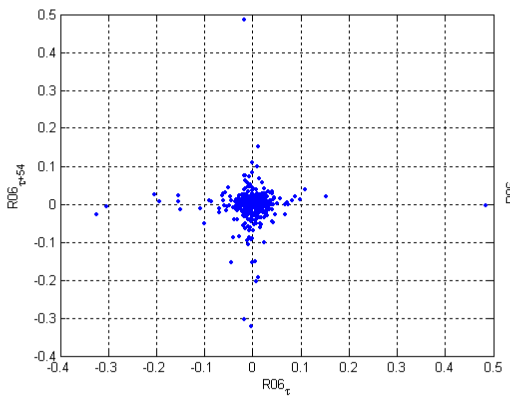

Fig. 4. Dec06 two-dimensional phase-space

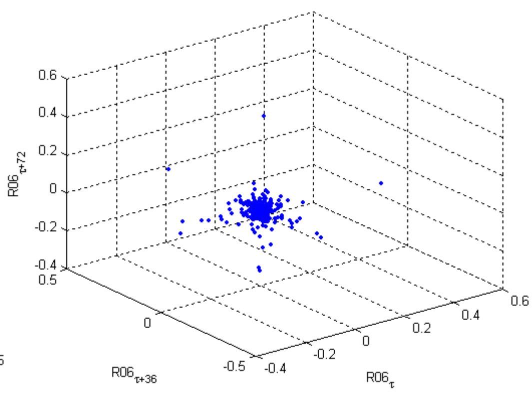

Fig. 5. Dec06 three-dimensional phase-space

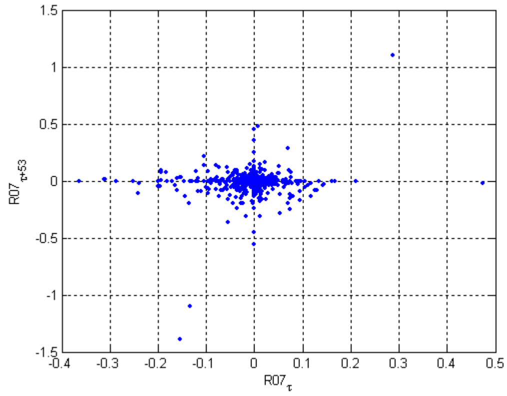

Fig. 6. Dec07 two-dimensional phase-space

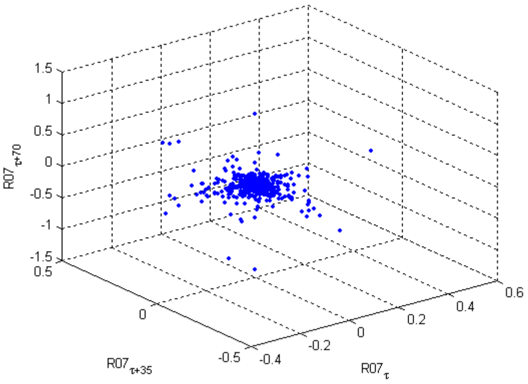

Fig. 7. Dec07 three-dimensional phase-space

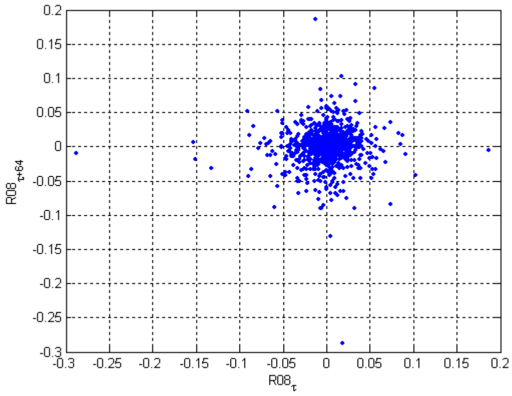

Fig. 8. Dec08 two-dimensional phase-space

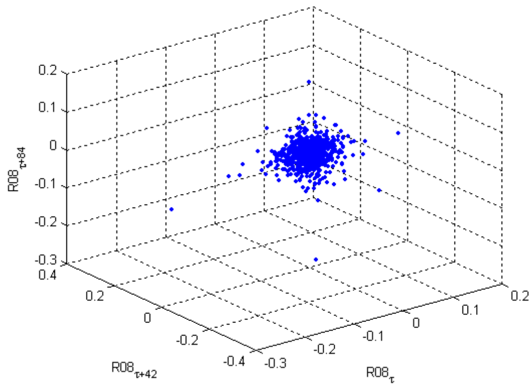

Fig. 9. Dec08 three-dimensional phase-space

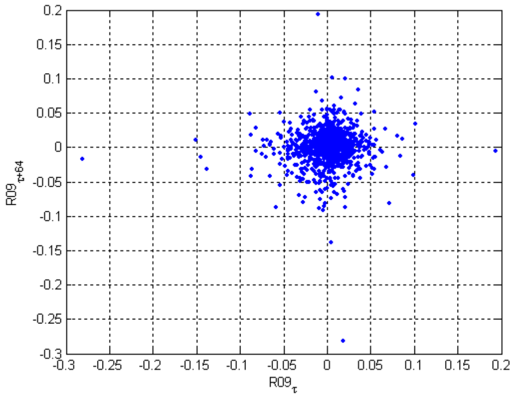

Fig. 10. Dec09 two-dimensional phase-space

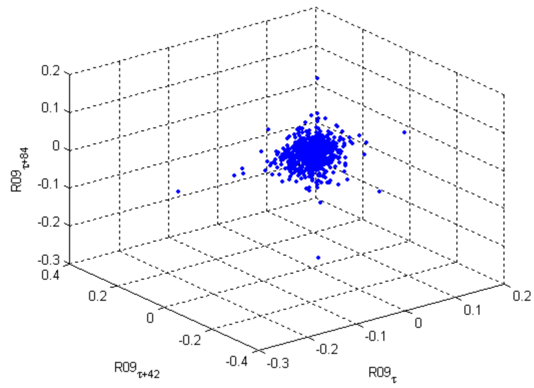

Fig. 11. Dec09 three-dimensional phase-space

Whether embedded in two-dimensional or three-dimensional space, the entire phase space is not filled with spots and maintains a certain attraction trend of carbon price (Figs. 2 to 11). The carbon price may be chaotic and an attractor.

The results of correlation dimension and maximal Lyapunov exponent are shown in Table 8 and 9.

Table 8

Correlation dimension of carbon price on the European Climate Exchange

m	Dec06(D)	Dec07(D)	Dec08(D)	Dec09(D)
2	0.1525	0.06313	0.2566	0.2562
3	0.2222	0.0856	0.3888	0.3846

4	0.3080	0.1165	0.5153	0.5110
5	0.4017	0.1428	0.6491	0.6420
6	0.4294	0.1630	0.7729	0.7630
7	0.5308	0.1858	0.8856	0.8752
8	0.5358	0.1981	0.9848	0.9711
9	0.5832	0.2301	1.1672	1.1567
10	0.6822	0.2444	1.1933	1.1819
Results	increasing	increasing	increasing	increasing

Note: m is embedded dimension.

The endogenous complexity of the nonlinear dynamics phenomenon of the volatility of carbon price is not obvious. From Table 8, we can see that the correlation dimension D is small and fractal and the carbon market system can be characterized by a small number of variables. Carbon markets thus have fractal characteristics. D increases with the growth of m, indicating that the carbon market system is a random time series corresponding to a random system, which is not an attractor in the phase space that has limited dimension.

Table 9

Maximal Lyapunov exponent of carbon price on the European Climate Exchange

m	Dec06	Dec07	Dec08	Dec09
2	0.7352	0.7001	0.8319	0.7489
3	0.5881	0.7209	0.4023	0.4192
4	0.6207	0.5613	0.2955	0.3416
5	0.4510	0.2783	0.2731	0.2498
6	0.3225	0.4243	0.2547	0.2552
7	0.3347	0.2756	0.2216	0.2271
8	0.2719	0.2193	0.1980	0.2074
9	0.2774	0.1687	0.2183	0.2146
10	0.2511	0.2051	0.1344	0.1518

Note: m is embedded dimension

From Table 9, the maximal Lyapunov exponent is greater than 0. A positive Lyapunov exponent is a basic feature of a chaotic attractor. The carbon market has chaotic properties, but not much significance for long-term carbon price forecasting. The Lyapunov exponent shows the decay rate of predictive capability. The second phase (Dec08 and Dec09) exponent is smaller than that of the first phase, indicating short-term prediction is slightly reliable.

Chaos theory analysis shows that there is no obvious complex endogenous non-linear dynamics in carbon price volatility. Carbon price fluctuation is between chaos and a random walk. Thus, the carbon market is mildly chaotic and shows market and fractal market characteristics.

5 Analysis of carbon price volatility

The above analysis illustrates that the EU carbon market is not a weak-form efficient market. The long-term memory of carbon price is not strong, short-term memory performance being more obvious. These findings demonstrate the complexity of the carbon market. What is the cause of the complexity of the carbon price volatility? We try to find the answer by analyzing the internal and external environments of the carbon market.

5.1 Impact of internal mechanism of the carbon market on carbon price volatility

Due to the short history and lack of participants, a feedback mechanism may be the most appropriate way to explain the volatility of carbon price.

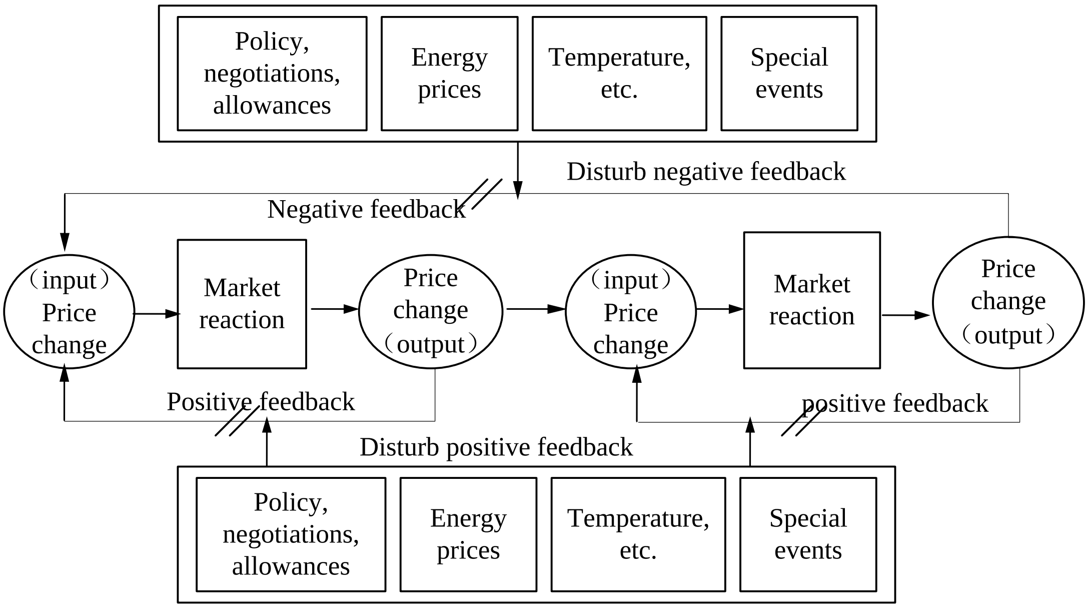

Fig. 12. Feedback mechanism of carbon price change in the European Climate Exchange

From Fig. 12, we can see that after the EU carbon market prices fluctuate, disturbance of the internal mechanisms responds timely to form a new price. Affected by the internal market mechanism, the new price changes again, leading to further changes of the market price. Such changes in price are caused by different traders and various disturbances.

There exists a market feedback mechanism during the EU carbon price fluctuation. Participants include positive feedback traders who purchase when the carbon price rises and sell when the price drops, and negative feedback traders who sell when the carbon price rises and buy when the price drops. Positive feedback traders are confident that there is room for the price to rise even when the price has been high, because the carbon market volume grows rapidly each quarter.

However, in the EU carbon market, the negative feedback effect becomes more apparent. People will sell contracts when prices are too high, and because of external uncertainties, for instance, contracts in the first phase do not cross into the second phase. current profit is the most important criteria. Therefore, high risk is obviously holding up long contacts. The existence of the feedback mechanism means the carbon price does not change as in a linear market. Under the impact of market information, the carbon price deviates from the basic price, and the market mechanism adjusts to the new price level in a relatively short time. Thus, carbon price have memory and the price fluctuation is not isolated, but interrelated.

According to the analysis, there is no obvious complex endogenous non-linear dynamics of carbon price fluctuation. Therefore, carbon price should have long-term memory, with carbon price volatility being caused by internal instability. Support in the empirical findings for long-term memory of carbon price is not clear (Table 5 and 6). The correlation dimension and the maximal Lyapunov exponent analysis indicate that the complex endogenous non-linear dynamics phenomenon of the EU carbon price fluctuation is not obvious (Table 8 and 9). This phenomenon makes the EU carbon market differ from the financial markets which have a feedback effect.

5.2 Impact of a heterogeneous environment on carbon market mechanisms

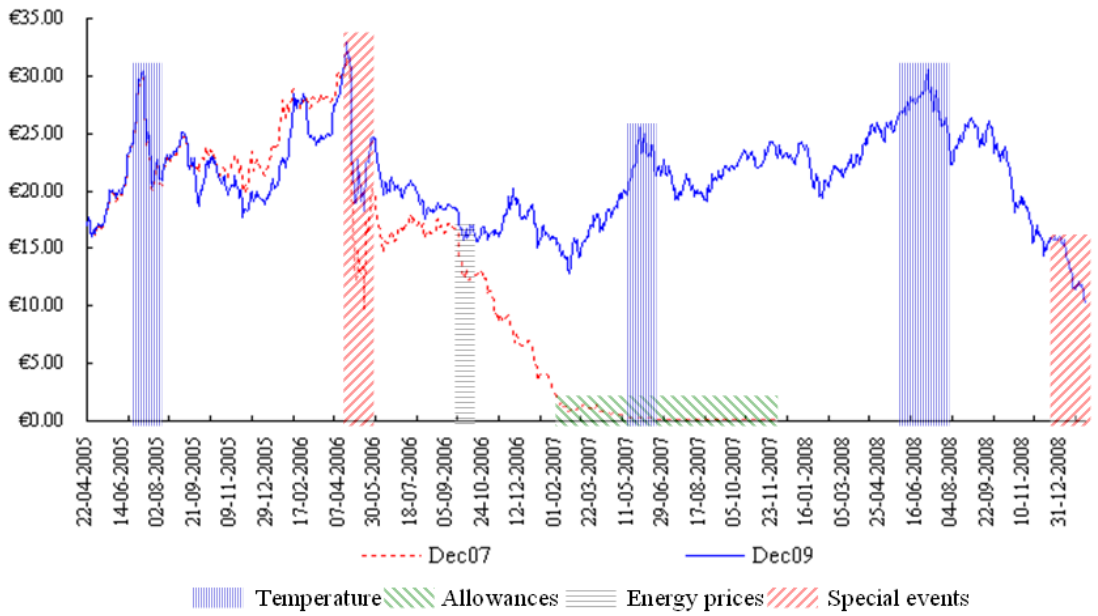

Fig. 13. Analysis of the heterogeneous environment of the carbon market

The external environment of the EU carbon market is complex. The price feedback mechanism has interruptions (see Fig. 12). Such interference should have a great impact on the carbon market. Zeeman [28] proposed a model of heterogeneous traders. In financial markets, heterogeneity is mainly reflected in traders. In the EU carbon market, heterogeneity reflected in traders is limited. Demand is relatively stable, and there are more changes in the external environmental factors such as international negotiations, allowances, weather temperature and demand for electricity. Thus, we consider the EU carbon market as a heterogeneous environment.

A heterogeneous environment impacts the market price by interfering in the internal feedback mechanism. As can be seen from Figure 13, when prices fall, the influence of the heterogeneous environment is more than that of the market itself.

(1) Temperature. Fifty-five percent of EUAs holders are in the heat and electricity sector. A cold, dry winter increases demand for heat and reduces generation from hydroelectric sources. Under such circumstances, coal generators are used to run plants, increasing the demand for EUAs, thus making EUAs "short". A hot, dry summer increases demand for electricity and water resources become scarcer. High

temperature may lead to more frequent stoppages of nuclear power plants. This in turn increases coal-fired electricity generation, which will increase emissions, thus causing carbon price to rise rapidly. Thus seasonal impact is obviously short-term. The results are same with both modified R/S and ARFIMA analysis (Table 5 and 6).

(2) Allowances. Greater allowances lead to lower demand and greater supply of carbon, leading carbon price to fall. Figure 13 shows the prices dropped to 0.01 tons per euro because of surplus allowances in the last few months of 2007 in the first phase. That is the reason why the memory of carbon price for Dec06 is more obviously than for Dec07, and the Hurst index of Dec06 is greater than that of Dec07: The carbon price was interrupted by too many allowances and did not have long-term memory (Table 5 and 6). At the same time, the second phase allowances are not surplus on current, the maximal Lyapunov exponent in second phase is small (Table 9), which indicates the short-term predictive capability in the second phase is better than the first phase. .

(3) Energy prices. For example, in September 2006, Germany used natural gas for power generation. Consequently, the price gap between natural gas and coal began to shrink, which also affected the market price and the feedback mechanisms.

(4) Special events (international negotiations, the financial crises, important notices etc.). As can be seen from Figure 13, the volatility of carbon price is greater in May 2006 that at any other time in the sample period because of the impact of the *May incident*（see section 1 in the paper）. Carbon price fell from 20 euros to less than 15 euros in the 2008 due to the global economic crisis. The economic recession reduced demand and reduced the output of enterprises which increased the number of carbon emissions permits. The carbon market supply increased, while demand reduced, resulting in a fall in the carbon price.

Therefore, the heterogeneous environment of the carbon market has a greater impact, disturbing the positive and negative feedback mechanisms and interfering in the long-term memory of the carbon price and affecting the price mechanism. Thus, the heterogeneous environment plays a leading role in the carbon market and carbon price volatility. Carbon price are not a random walk, long-term memory is weak, and there is no obvious complex endogenous nonlinear dynamics in the carbon market. Therefore, we believe that EU carbon price fluctuation is caused by market mechanisms, made complex by the external heterogeneous environment.

6 Conclusions

In this paper, we use nonlinear dynamics theory to analyze carbon price volatility in the carbon market. Our main findings are as follows:

(1) The traditional theory of a weak-form efficient market does not describe the basic characteristics of the carbon market. Carbon price history information is not totally reflected in the current carbon price. The carbon market is not a weak-form efficient market. The market exhibits heteroscedasticity properties and carbon price such as Dec07 do not support the null hypothesis (RW1) at the 95% level and is not a random walk, but a biased random, which may lead to high volatility of carbon price such as the *May incident* and the later period in 2007, the authorities can propose carbon price floors against it, low carbon price will be a disadvantage to carbon emission reduction, for carbon price are determined by the marginal emission

abatement costs in economic theory.

(2) R/S and modified R/S analysis show that the carbon market is a biased random walk and has some characteristics of fractal markets. The history information of prices is not fully reflected in current carbon price. R/S and ARFIMA analyses support that the long-term memory of carbon price is not obvious. The influence of carbon price history on the future trend of carbon price is short.

(3) Chaos theory shows the correlation dimension is increasing with embedded dimensions, indicating that the carbon market system is not an attractor and that there is no obvious complex endogenous nonlinear dynamics in the market. The maximal Lyapunov exponent greater than 0.1 indicates that the carbon market is chaotic, indicating both market and fractal market characteristics. Long-term carbon price forecast does not have much significance because of the maximal Lyapunov exponent being large. The second phase short-term forecast is better than the first phase for the maximal Lyapunov exponent is smaller than the first phase, which shows the second phase run better.

(4) In the carbon market mechanism, i.e., the positive and negative feedback mechanisms and the heterogeneous environment, carbon price fluctuation is complex. The impact of the endogenous mechanisms and the feedback mechanisms causes carbon price fluctuations. In particular, heterogeneous environmental features such as temperature, allowances, energy prices and special events would affect the carbon price, causing substantial fluctuations, making carbon price complex. This indicates a requirement to implement practices to regulate and develop the carbon market. Regulatory rules can be set up to take advantage of market mechanism and eliminate the heterogeneous environment, which would be beneficial to carbon market development.

The paper argues that the carbon market is weak and unstable despite having general market characteristics. Regulators can consider the price volatility trend and reasons, the heterogeneous environment of carbon market to improve the situation and develop carbon market. At the same time, the paper provides a new key to understand carbon market system from dynamic, nonlinear perspective. We expected to expand the existing carbon price volatility theory in order to explain and guide carbon market better. Carbon price data was used in the paper, however, more complicated date such as energy prices and temperature could be considered in the empirical analysis and the behavior of the stakeholders could be investigated for future research.

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