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How does carbon price change? Evidences from EU ETS

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Abstract: By proposing the hypotheses for carbon price volatility, this paper uses variance ratio and Ensemble Empirical mode decomposition (EEMD) to analyze the carbon price. Results show that carbon price is influenced by temperature, market mechanism and heterogeneous environment. Carbon market is temperature-sensitive, affected by seasonal changes, which presents a style of movement amplitude; Carbon price is affected by the market mechanism at a high frequency, with the duration being less than 15 weeks and amplitudes less than 5 euros. Heterogeneity environment has an impact on carbon price at a low frequency, the duration lasting more than 34 weeks or even more and amplitudes more than 10 euros or higher. Meanwhile, the analysis for historical carbon price change shows the long term trend declines gradually since 2005 from 18 to 16 euro per ton. The continuing declining trend agrees with special events by time. Our research explores the reasons of carbon price volatility and some recommendations are given trying to regulate carbon market.
Keywords: carbon price; Ensemble Empirical Mode Decomposition; variance ratio; price volatility; temperature sensitivity

I Introduction

With CO2 emissions having become a scarce resource, the international CO2 emissions trading market (carbon market) has developed rapidly. Trading volume under the European Union Emissions Trading Scheme (EU ETS) increased from 8.49 million tons in 2004 to 6326 million tons in 2008, and the trading value increased from US$8.2 billion in 2005 to US$1184.74 billion in 2009 [1,2]. Carbon price has significant effects on global CO2 emissions reduction and is known for its wide swing.

There are several studies on carbon price analysis, such as the relationship between carbon price, other energy prices and industrial production [3]. For example, Alberola et al. [4] 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 have showed that the carbon price was not only influenced by energy prices and forecast error, but also by unanticipated weather temperature. Chevallier [5] explained the relationship between EU ETS carbon futures and macroeconomic factors. He used GARCH (p, q), ARCH and TGARCH models to analyze carbon futures return change under macroeconomic conditions. Analysis has shown that the EU emissions allowances (EUAs), as a new type of

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commodity, are obviously influenced by electricity demand. Oberndorfer [6] researched the effects of the power companies' stock prices in EU ETS. The results showed that carbon prices were positively correlated with stock prices, although this effect was not asymmetric. Benz and Truck [7] established Markov switching and AR-GARCH models to study the returns of emission allowances. Wei et al. [8, 9] studied the relationship between carbon price and energy prices including power, oil, coal and natural gas. Alberola et al. [10] confirmed the impact of variations in industrial production on EUA price changes in Germany, Spain Poland and the UK. Feng et al. [11] studied the carbon price volatility from a nonlinear dynamics point of view, the analysis shown that some factors impact on carbon price.

Under the influence of market mechanisms and uncertainty factors, the carbon price analysis is complex. Traditional methods are difficult to describe the carbon price analysis. The econometric models can help understand the mechanisms of carbon price determination and quantify each factor's impact on carbon price [4]. However, this approach was difficult due to some specific characteristics of carbon market. For example, carbon supply is hard to model because it is dynamic and unstable. Some others methods such as Data-driven methods often perform well but they lack economic meaning and cannot explain the inner driving forces that move carbon price.

The dilemma between difficulties in modeling and lack of economic meaning can be solved by an objective data analysis method, i.e. Ensemble Empirical Mode Decomposition (EEMD) [12], is an empirical, intuitive, direct and self-adaptive data processing method which is proposed especially for nonlinear and non-stationary data, EEMD not only helps discover the characteristics of the data but also helps understand the underlying rules of reality.

In this paper, we analyze carbon price and find that it can help interpret the formation of carbon price from a novel perspective. At first, it has already been tested that carbon price is temperature-sensitive in the literature from econometric models, we will re-verify it. At the same time, we give the hypotheses of carbon price is influenced by carbon market internal mechanism and heterogeneous environment and test the hypotheses.

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

2 Methodologies

Some researches supported carbon market is temperature-sensitive. Mansanet-Bataller et al. [13] show empirical evidence of the impact of weather variables on CO2 price changes. Alberola et al. [4] and Feng et al. [11] argue that the impact is obviously. Indeed, more than 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. The paper will re-verify it, and then use the carbon price after seasonal adjustment.

According to the fluctuation of carbon price, the paper will give the following hypotheses:

2.1 Hypotheses

Hypothesis 1: Market mechanism impact carbon price, the frequency is high, duration is short and the amplitude is small.

The carbon market has some common attributes of markets, carbon price will rise when the carbon allocation demand is strong, otherwise carbon price maybe down, The normal market fluctuations is caused by normal supply-demand disequilibrium, such as disequilibrium of supply-demand, have no serious impact carbon price, it is generally within few euro(*the amplitude is small*), But these events are becoming more and more frequent (*the frequency is high*) and the influence of these events lasted for only several weeks (*the duration is short*). Chevallier [5] shown carbon price are obviously influenced by electricity demand, which will lead a carbon allocation demand.

Hypothesis 2: heterogeneous environment impacts the market price by low frequency, long duration and high amplitudes.

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).

The frequency of heterogeneous environment occurring is less, but the impact is large, carbon price change may exceed 10 euros (May event) in short time; and , the duration lasting several months such as the financial crisis in 2008. The analysis may help us to understand carbon price fluctuation deeply.

2.2 Methodologies

The paper uses variance ratio proposing by Lo and MacKinlay [14, 15] to verify carbon market is temperature-sensitive. The principle of the variance ratio test is as follows: If carbon price was a random walk process, then the variance of period K should be k-fold the sample period. If the carbon market is temperature-sensitive which is affected by the season, then the results of variance ratio in the spring and autumn, summer, winter trend are different. In this paper, we build variance ratio statistics for analysis according to whether the carbon price is homoscedastic (RW1) or heteroscedastic (RW3).

The paper uses seasonal adjustment method to analyze the temperature-sensitive by comparing the original carbon price and the price after the seasonal adjustment. The seasonal adjustment methods was proposed by Wheelwright et al. [16]

The length for $x(t)$ is n, corresponding to the seasonal cycle of M, the moving average named MA is defined by:

$$MA(t+\frac{M-1}{2})=(x(t)+x(t+1)+\cdots+x(t+M-1))/M$$

The average of MA is:

$$MMA(t+\frac{M}{2})=\frac{1}{2}\left[MA(t+\frac{M-1}{2})+MA(t+\frac{M+1}{2})\right]$$

the scale factor is

$$Ra(t+\frac{M}{2})=x(t+\frac{M}{2})/MMA(t+\frac{M}{2})$$

Let calculate the mean of Ra for the same season, then adjust the Ra, making the mean of the sum of Ra is equal to M. the seasonal series can be obtained by dividing Ra with the original series.

After the seasonal adjustment, the carbon price will be applied EEMD, an improved Empirical mode decomposition (EMD) developed by Huang et al. [17]. EMD can deal with price volatility better, EMD has adaptive characteristics, and the decomposition of carbon price series can reflect the characteristics of the original price. The results show that, EMD method can described carbon price fluctuation [18-20]. The EEMD improved EMD by overcoming the frequent appearance of mode mixing.

EMD can extract these intrinsic modes from the original carbon price time series, based on the local characteristic scale of data itself, and represent each intrinsic mode as an intrinsic mode function (IMF), which meets the following two conditions:

(1) The functions have the same numbers of extreme and zero-crossings or differ at the most by one;

(2) The functions are symmetric with respect to local zero mean.

The EMD algorithm is described as follows:

(1) Identify all the maxima and minima of carbon price time series $x(t)$, generate its upper and lower envelopes, making all the carbon price are between the two envelopes.

(2) Calculate the point-by-point mean ($m(t)$) from upper and lower envelopes. Extract the mean from the time series and define the difference of $x(t)$ and $m(t)$ as $h(t)$:

$$h(t)=x(t)-m(t)$$

(3) If $h(t)$ is an IMF, denote $h(t)$ as the ith IMF and replace $x(t)$ with the residual $r(t)=x(t)-h(t)$. the ith IMF is often denoted as $c_i(t)$ and the i is called its index, which define $c_i(t)=h(t)$.

(4) Repeat steps (1)-(4)

One stopping criterion proposed by Huang et al. [18] for extracting an IMF is: (1) the component $c_i(t)$ or the residue $r(t)$ becomes so small that it is less than the predetermined value of a substantial consequence; (2) the residue $r(t)$ becomes a monotonic function from which no more IMFs can be extracted. The carbon price time series can be expressed:

$$x(t)=\sum_{i=1}^{N}c_i(t)+r(t)$$

Where N is the number of IMFs, $c_i(t)$ is the IMF and $r(t)$ means the final residue. In the sifting process, the first component, c_1, contains the finest scale (or the shortest period component) of the time series. The residue after extracting c1 contains longer period variations in the data. Therefore, the modes are extracted from high frequency to low frequency. Thus, EMD can be used as a filter to separate high frequency (fluctuating process) and low frequency (slowing varying component) modes.

EMD can extract the carbon price time series trend or remove the mean of the time series effectively [12, 20]. The IMFs have a clear instantaneous frequency as the derivative of the phase function, so Hilbert transformation can be applied to the IMFs, allowing us to analyze the data in a time-frequency-energy space. However, the original EMD has a drawback: the frequent appearance of mode mixing, which is defined as a single IMF either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF components.

The basic idea of EEMD is adding a white noise series to the targeted data, each observed data is amalgamations of the true time series and noise. Thus even if data are collected by separate observations, each with a different noise level, the ensemble mean is close to the true time series. Therefore, an additional step is taken by adding white noise that may help extract the true signal in the data.

The effect of the added white noise can be controlled according to the well-established statistical rule.

$$\varepsilon_n=\frac{\varepsilon}{\sqrt{N}}$$

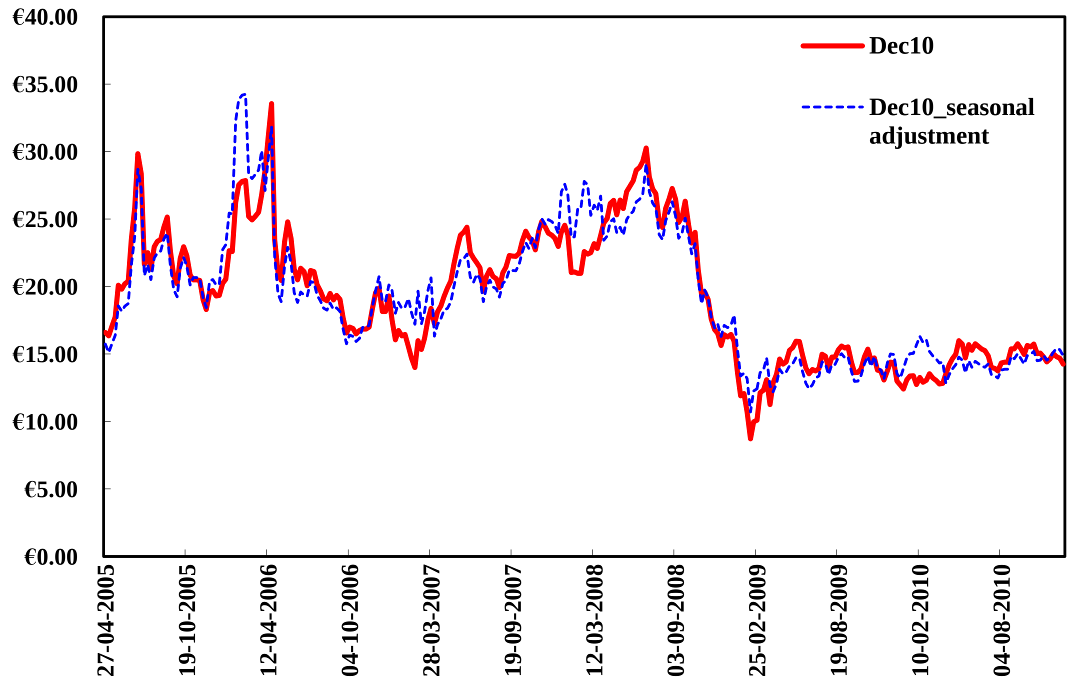
Where N is the number of ensemble members, ε is the amplitude of the added noise, and ε_n is the final standard deviation of error, which is defined as the difference between the input carbon price signal and the corresponding IMFs.

In response to the carbon frequency and amplitude of price changes, the frequencies of IMFs are from low to high and amplitudes are from small to big. The high frequency component is impacted by the market mechanism, and the influence is short-term [20]. The low frequency component is impacted by the heterogeneous environment, whose influence is long [20]. We use the frequency of IMFs to analyze the hypothesis 1 and 2.

3 Data

The paper uses the data from the, the European Climate Exchange (ECX), Netherlands. The major carbon price series are selected for the study: future that delivery December 2010 (Dec10 for short). We use the weekdays selected from the following periods: April 2005 to Dec 2010. The futures prices of Dec08, Dec09 and Dec10 are very similar in 2005, 2006 and

2007 (the EU ETS first phase), Dec10 delivered in 2010, which can representative carbon price during 2005 to 2010. The carbon price trend is shown in Fig. 1.



Note: The original price shown in the red solid line and the blue dotted line represent the price after seasonal adjustment.

Fig. 1 Carbon (CO_2) price of the European Climate Exchange for Dec10

4 Results and discussions

4.1 Re-verify seasonal Impact on carbon price

The analysis of variance ratio for Dec10 shows in Table 1.

Table 1

The results for variance ratio

Observed	Num. Obs.	Price mean	Price Stand. dev.	Variance Ratio VR	Variance Ratio $\psi(q)$	Variance Ratio $\psi^*(q)$
			Panel A: weekdays			
Normal [a]	603	19.10	4.73	1.01	0.23	0.16
Summer [a]	523	20.18	4.73	1.21	3.22***	3.13***
Winter [a]	323	17.72	4.77	1.11	1.32	1.61
Monday	282	19.21	4.89	0.96	-0.40	-0.36
Tuesday	293	19.17	4.87	1.03	0.38	0.32
Wednesday	294	19.14	4.80	1.15	1.76	1.32
Thursday	292	19.20	4.81	1.05	0.52	0.35
Friday	288	19.19	4.77	1.03	0.33	0.22
			Panel B: weekdays			

Original	1449	19.18	4.82	1.20	3.05***	1.97**
Prices(adjustment)	1449	19.21	4.86	1.04	1.09	0.80

Note: a. Normal months include March, April, May, October and November. Summer includes June, July, August and September. Winter is defined as December, January and February.

b. $\psi(q)$ and $\psi^*(q)$, respectively, are the variances of the homoscedastic and heteroscedasticity-adjustment 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.

Carbon market is temperature-sensitive, impacting by seasonal and showing a type of movement amplitude. Carbon rice in summer does not support the null hypothesis (RW1) at the 99% level and is not a random walk, the price in the spring and winter is a random walk under the same circumstances (Table 1). The price does not support the null hypothesis (RW3) after heteroscedasticity adjustment. Several major increasing for carbon price is relationship with temperature, and the trend of carbon price increase in summer and decline in autumn.

The carbon price is divided by Monday, Tuesday, Wednesday, Thursday and Friday. The carbon price from Monday to Friday accepts the random walk hypothesis and is a random walk (Table 1). When we mix carbon price, the carbon price accept the random walk hypothesis. The conclusion support the carbon market is temperature-sensitive.

Dec10 does not support the null hypothesis (RW1) at the 95% level but shows a random walk after heteroscedasticity adjustment (Table 1). Therefore, the seasonal temperature impacts the carbon market. The paper will use the carbon price after seasonal adjustment to analyze and the carbon price after seasonal adjustment shows in Fig. 1.

4.2 Statistics analysis for carbon price EEMD

Carbon price data series can be decomposed into a set of independent IMFs with different scales, plus the residue through EEMD. The results can be shown in Fig. 2 and Table 2.

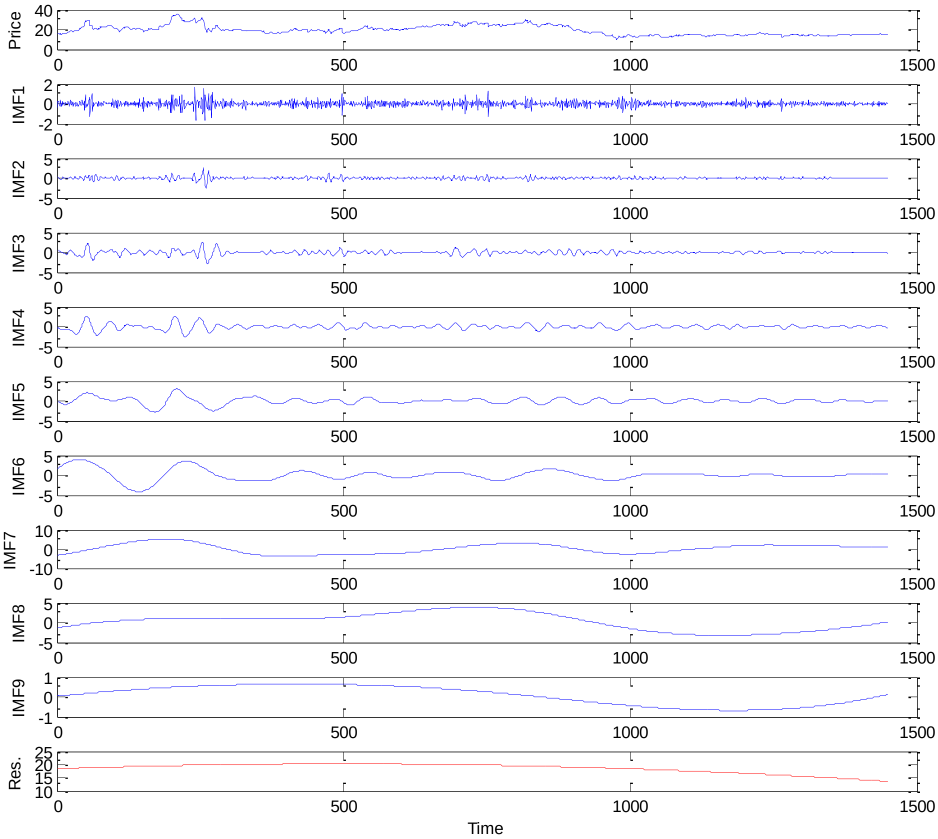


Fig. 2 The IMFs and residue for the carbon data from April 2005 to Dec 2010 derived through EEMD.

Table 2

Summary statistics for Dec10 derived through EEMD

	Mean period (week)	Pearson correlation	Kendall correlation	Variance	Variance as % of observed	Variance as % of (IMFs+residual)
Observed				23.57		
IMF1	0.71	0.06*	0.04*	0.08	0.34%	0.46%
IMF2	1.49	0.12**	0.07**	0.10	0.42%	0.58%
IMF3	3.33	0.19**	0.11**	0.25	1.06%	1.45%
IMF4	6.13	0.22**	0.12**	0.43	1.83%	2.49%
IMF5	14.53	0.26**	0.14**	0.66	2.80%	3.82%
IMF6	34.5	0.30**	0.18**	1.90	8.06%	11.01%
IMF7	110.40	0.40**	0.22**	5.95	25.25%	34.47%
IMF8	138	0.77**	0.61**	4.51	19.14%	26.13%
IMF9	276	0.61**	0.33**	0.22	0.93%	1.27%
Residual		0.60**	0.35**	3.16	13.41%	18.31%
Sum					73.26%	100.00%

*、**correlation is significant at 0.05, 0.01 level, respectively. (2-tailed)

The analyses for IMF statistics show that:

(1) In response to the carbon frequency and amplitude of price changes, the frequencies and amplitudes of IMFs are from low to high. The mean period is defined as the value derived by dividing the total number of points by the number of peaks for each IMF since the frequency and the amplitude of an IMF may change with time continuously and the periods are also not constant. Two correlation coefficients, Pearson product moment correlation coefficient and Kendall rank correlation coefficient are used to measure the correlations between IMFs and the observed data from different points of view [20]. These IMFs are independent of each other and the relationship between IMFs and the trend term is independent, However, the variances of IMFs and the residue do not always add up to the observed variance, due to a combination of rounding errors, nonlinearity of the original time series and introduction of variance by the treatment of the cubic spline end conditions [21].

(2) The average cycle of IMF1, IMF2, IMF3, IMF4 and IMF5 are short, Kendall coefficient is significant, indicating IMF1 and IMF2 has little impact on the long-term trend of carbon price. The correlation for IMF6 to IMF 9 in component is high, indicating that IMF6 to IMF9 impact on the long-term trend of carbon price, the Pearson coefficient also reach a high level. The residue is often treated as the deterministic long term behavior overarching trend for carbon price is declining because carbon price has been in decline from 2008 during the financial crisis.

(3) The mean of the fine-to-coarse reconstruction departs significantly from zero at IMF6. Therefore, the partial reconstruction with IMF1 to IMF5 represents high frequency component and the partial reconstruction with IMF6 to IMF9 represents the low frequency component.

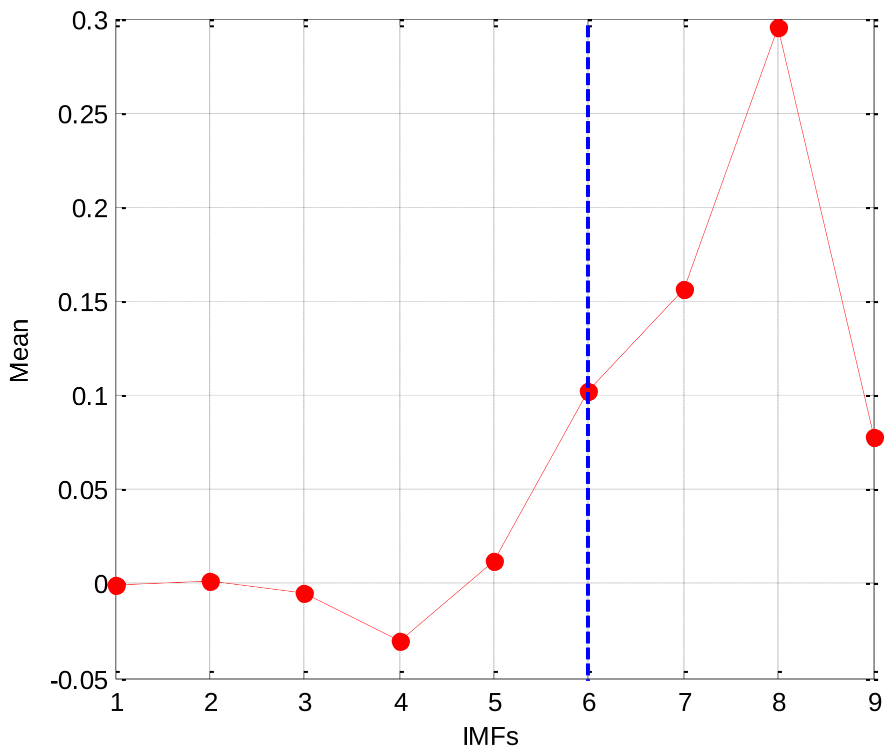


Fig. 3 The mean of the fine-to-coarse reconstruction as a function of index K. The vertical dash-line at K=6 indicates that the mean departs significantly from zero

(4) According to the analysis in section 2.2, the volatility of high frequency component with IMF1 to IMF5 is impacted by the market mechanism and the influence time is less than 15 weeks. The low frequency component is influenced by the external environment and the influence time is more than 34 weeks.

4.3 Impact of market mechanism on carbon price volatility

The markets' normal fluctuation is small and frequency is high, the effect is generally within 5 euro, the time may endure less than 15 weeks (Fig. 2, 4).

Carbon market has the general market properties, such as such as disequilibrium of supply-demand. Power plants are the main participants in the carbon market, the more the power demand, the more the allowances need. The allowances change affects the market supply, which will affect the carbon price. In September 2006, Germany used natural gas as main fuel for power generation. Consequently, the price gap between natural gas and coal began to shrink, which also affected the disequilibrium of supply-demand price and price. Therefore, the allowances supply and demand in market mechanism are influenced by energy prices and industrial production. Chevallier [5] showed that power demand affecting carbon price. On the other hand, due to high transactions frequency, the durations of price declining and rising are short.

Within the 5 euros, though the amplitudes are small and the duration is short, but it is very important in the short-term forecast because the frequency is high, leading carbon price fluctuation is large. Indeed, the hypothesis 1 is reasonable according to the analysis.

4.4 Impact of heterogeneous environment on carbon price volatility

EU carbon market has running from April 2005 and it is divided into three phases, the carbon market is in a complex external environment. The heterogeneous environment includes international negotiations, special events, etc. (not including climate change). International negotiations have a great impact on quota allocation, which impact carbon price. The effects of heterogeneous environment are mainly described by IMF6 to IMF9 (Fig. 2). Looking at the mean periods of these IMFs, the shortest is more than 34 weeks and the longest can be as long as 1 year.

Carbon price is influenced by special events such as important news releases and financial crisis. In May 2006, the May incident made carbon price volatility large, this component resulted in a price decline of €13, which means the maximum effect and of the events was €13 and time lasting more than 2 month. The global economic crisis starts at September 2008, making the demand of allowances down, and carbon price falling from 20 euros to 15 euros. It did not return until the Mar of 2009 (Fig. 2, 4).

The frequency of heterogeneous environment occurring is less, but the influence is large, the long lasting time suggest that it is hard for the market itself to eliminate these effects soon; the duration of the effect of a special event may be very long. In addition, the amplitudes at some data points could be more than €10 or even higher. The impact of external influence on the carbon market is greater than the market mechanism. Therefore, we argue that hypothesis 2 is reasonable.

By separating special events as the low frequency component from the whole price, the effect of every special event can be measured and the result can then be a reference for forecasting the effect of the next significant event of the same type. For example, the amplitudes at financial crisis in 2008 could be more than 10 euros or even higher, suggesting that the effects of some significant events on carbon price may be very serious, the price did not return until the Mar of 2009. Since no serious event occurred during this period, we can conclude that the influence of the event lasted for 7 months.

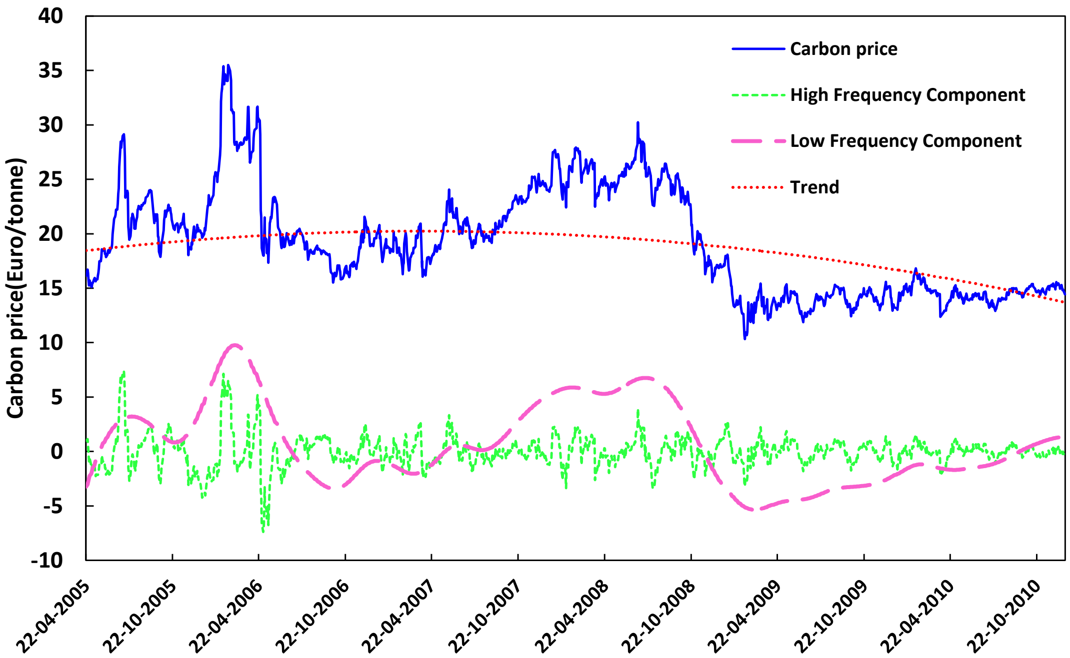


Fig. 4 Three components of the carbon price series

4.5 Trend for carbon price

According to Zhang et al. [20], the res. for EEMD (Fig. 2 Res.) is a long-term trend for carbon price. The heterogeneous environment leading to a significant change, the trend of carbon price declines gradually since 2005 from 18 euro per ton to 16 euro per ton.

From the comparison of the trend with the observed price, the continuing declining trend agrees with the May accident in 2006 and financial crisis of the world in 2008 by time, which may imply that the long term trend of carbon price is determined by special events. The analysis shows that the overall price of carbon prices has some mild change, declining gradually since 2005 from 18 euro per ton to 16 euro per ton.

The trend holds a high correlation with the original price and accounts for 13% of variability, suggesting it is not a deterministic force for carbon price evolution in the long run.

5 Conclusions

The paper use variance ratio and Ensemble Empirical mode decomposition (EEMD) to analyze the carbon price volatility factors from market mechanism, heterogeneous environment and temperature. The results show:

(1) The carbon market is temperature-sensitive, affected by seasonal changes, which presents a style of movement amplitude. The paper gets some factors that impact carbon price from EEMD, which shows as IMFs and trend. The decomposition confirms carbon price is influenced by market mechanism, heterogeneous environment and carbon price trend. Carbon price affected by the market mechanism at a high frequency, the duration generally less than 15 weeks and amplitudes is less than 5 euros. Heterogeneity environmental impact carbon price at a low frequency, the duration is more than 34 weeks or even more and amplitudes is usually more than 10 euros or higher.

(2) The analysis for carbon price changes shows that the long term trend declines gradually since 2005 from 18 euro per ton to 16 euro per ton. The continuing declining trend agrees with special events by time.

By analyzing the composition of carbon price, some forecasting strategies can be considered: the first is to get low frequencies IMFs, high frequencies IMFs and trend; the second might be grouping the IMFs into a nonlinear part and a linear part, forecasting each individually, and then summing them up together. The trend can be predicted by fitting the curve and the short term fluctuations can be dealt with nonlinear forecasting techniques [20]. High frequency IMFs can be predicted by analyzing market participants and the system of market access. Low frequencies forecasting is difficult because heterogeneous environment itself is influenced by many factors, such as political situation, allocations and other complicated factors. No one knows when and where, what will happen. But EEMD gives us some new method or an integrated forecasting framework to handle these issues and other prices.

Regulators can develop and improve carbon market through taking the trend and reasons of price volatility, the heterogeneous environment of carbon market into consideration, in order to make them a critical part of carbon emissions reductions.

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