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Carbon price analysis using empirical mode decomposition

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Abstract: Mastering the underlying characteristics of carbon price changes can help governments formulate correct policies to keep efficient operation of carbon markets, and investors take effective measures to evade their investment risks. Empirical mode decomposition (EMD), a self-adaption data analysis approach for nonlinear and non-stationary time series, can accurately explain the formation mechanism of carbon price by decomposing it into several intrinsic mode functions (IMFs) and one residue from different scales. In this study, we apply EMD to the European Union Emissions Trading Scheme (EU ETS) carbon price analysis. First, the carbon price is decomposed into eight IMFs and one residue. Moreover, these IMFs and residue are reconstructed into a high frequency component, a low frequency component and a trend component using hierarchical clustering method. The economic meanings of these three components are identified as short term market fluctuations, effects of significant trend breaks, and a long-term trend, respectively. Finally, some strategies are proposed for carbon price forecasting.

Keywords: Carbon Price; Empirical Mode Decomposition; Multiscale Analysis; Forecasting; EU ETS

1. Introduction

On February 16, 2005, the Kyoto Protocol came into force, which states that the European Union (EU) is committed to reducing greenhouse gas emissions by 8% below its 1990 level during the period 2008-2012. In order to meet the commitment at the lowest overall costs, also in 2005, the EU Emissions Trading Scheme (EU ETS) was launched within the EU covering around 12,000 installations in 25 countries and 6 major industrial sectors. In terms of market value and trading volume, the EU ETS is the largest carbon market all over the world up to date [1]. Therefore, we focus on the EU ETS carbon price analysis in this study.

During the past few years, there have been some studies on the analysis and forecasting of EU ETS carbon prices. These empirical approaches can be grouped into two categories: structured models and data-driven models. The structured models outline the carbon markets characteristics, and then analyze the carbon price movements mainly from the perspective of supply-demand equilibrium [1, 2]. Data-driven models include linear models such as Multivariate Linear Regression (MLR), Autoregressive Moving Average (ARMA), Vector Autoregressive (VAR), Granger Causality Test, Autoregressive Conditional Heteroscedasticity (ARCH), Generalized ARCH (GARCH), Threshold GARCH (TGARCH) and Markov Switching–AutoRegressive-GARCH models [3-5], and nonlinear models such as Differential Equation [6], Rescaled Range (R/S) analysis [7]. There are a number of other references on this topic [8-19].

The structured models can help us understand the generation of carbon prices, and estimate each factor's impact on carbon prices. However, this approach has proved to be difficult to be implemented in practice, because

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that it is hard to model the supply and demand under the dynamic and unstable market environment. Data-driven methods often perform well for short-term carbon price forecasting, but they lack the economic meaning and cannot well explain the inner driving forces of carbon price movements.

Empirical mode decomposition (EMD) [20], a self-adaption data analysis approach for nonlinear and non-stationary time series, proposed by Huang *et al.* in 1998, can solve the dilemma between the difficulties in modeling and the lack of economic meaning. EMD can decompose carbon prices into several independent intrinsic mode functions (IMFs) and one residue based on local characteristic scales [21]. Thus, we can identify the concrete implications of each IMF and the residue according to its own scale. For example, an IMF with a scale of three months can be recognized as the seasonal component. Since the carbon price is the only link we have with the reality, via exploring data's IMFs, EMD can help not only discovering the characteristics of carbon prices but also understanding the underlying rules of carbon prices. Therefore, EMD is effective for nonlinear and non-stationary carbon price analysis.

EMD was initially proposed for the study of ocean waves, and then successfully applied in many areas, including biomedical engineering, structured health monitoring and earthquake engineering. In recent years, there have been some successful applications in social sciences so far. Huang *et al.* applied EMD to financial data to examine the changeability of the markets [22]. Zhang *et al.* adopted EMD for West Texas Intermediate (WTI) crude oil spot price analysis [23]. Yu *et al.* applied EMD for financial crisis forecasting [24]. Zhu applied EMD for carbon price forecasting [25]. Moghtaderi *et al.* analyzed trend filtering by EMD with applications to environmental studies and bicycle rental services [29]. In this study, we will show that EMD can be useful for carbon price analysis.

The contributions of this paper are twofold. Firstly, we carry out an EMD-based multiscale analysis for the carbon price which is decomposed into several IMFs and one residue, from high to low frequency. These IMFs and residue are reconstructed into a high frequency component, a low frequency component and a trend component by hierarchical clustering method. The economic meanings of these three components are identified as short term fluctuations, effects of significant trend breaks, and a long-term trend, respectively. Secondly, according to the results of the carbon price analysis, we propose some forecasting strategies for carbon prices. All components are predicted based on their own features, and then integrate their results to obtain a final result of the original carbon price. Numerical details on the computational steps to obtain the results in the Matlab 2013a software are included in the paper.

The main motivation of this study is to apply EMD for carbon price analysis and attempt to interpret the formation mechanism of carbon price from a novel perspective. The rest of this paper is organized as follows: Section 2 outlines EMD and hierarchical clustering method; Section 3 introduces the EU ETS carbon price data and decomposes them by EMD. The derived IMFs are also shown in this section. Section 4 presents some analyses based on a composition using the hierarchical clustering method. Section 5 concludes this paper.

2. Methodology

2.1. EMD

EMD assumes that the carbon price simultaneously has many IMFs of different oscillations. Each IMF can be extracted from carbon price based on local characteristic scale of carbon price itself. IMF meets two conditions

[20]: ① IMF has the same number of extremum and zero-crossings or differs by one at the most; ② IMF is symmetric with the local zero mean. EMD can extract the IMFs through a sifting process as follows:

- (1) Identify all the maxima and minima of carbon price data $x(t)$;
- (2) Generate their upper and lower envelopes, $e_{\max}(t)$ and $e_{\min}(t)$, with cubic spline interpolation;
- (3) Calculate the point-by-point mean $m(t)$ from the upper and lower envelopes:

$$m(t) = \frac{e_{\max}(t) + e_{\min}(t)}{2}$$

- (4) Extract the mean from carbon price data and define the difference between $x(t)$ and $m(t)$ as $d(t)$:

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

- (5) Check the properties of $d(t)$:

① If it is an IMF, denote $d(t)$ as the i th IMF and replace $x(t)$ with the residue $r(t) = x(t) - d(t)$. The i th IMF is often denoted as $c_i(t)$ and the i is called its index;

- ② If it is not an IMF, replace $x(t)$ with $d(t)$;

(6) Repeat steps (1) – (5) until the residue satisfies some stopping criteria. One typical stopping criterion proposed by *Rilling et al.* [26] introduces the mode amplitude $\alpha(t) := \frac{e_{\max}(t) - e_{\min}(t)}{2}$, and the evaluation

function $\sigma(t) := \left| \frac{m(t)}{\alpha(t)} \right|$. Thus the sifting is iterated until $\sigma(t) < \theta_1$ for some prescribed fractions $(1 - \alpha)$ of the total duration, while $\sigma(t) < \theta_2$ for the remaining fractions, where θ_1 and θ_2 are two thresholds aimed to guarantee globally small fluctuations in the mean while taking into account locally large excursions. One can typically set $\alpha = 0.05$, $\theta_1 = 0.05$ and $\theta_2 = 0.5$.

At the end of this sifting procedure, the carbon price $x(t)$ can be expressed as

$$x(t) = \sum_{i=1}^m c_i(t) + r_m(t)$$

where m is the number of IMFs, $r_m(t)$ is the final residue, and $c_i(t)$ represents the i th IMF.

2.2. Hierarchical clustering method

The main aim of clustering analysis is to identify variables on some features of similar or dissimilar, and according to these features variables are divided into several categories. There are many clustering analysis methods, among which hierarchical clustering method [27] is one of the most commonly used.

After decomposing the carbon price into $m + 1$ IMFs (including one residue) by EMD, a high frequency component, a low frequency component and a trend component can be obtained from the hierarchical clustering method:

- (1) Calculate the distance between any two IMFs, which can be selected from the Euclidean distance, Chebychev distance, Minkowski distance, and so on.
- (2) Divide each IMF into a category, and get $m + 1$ categories.
- (3) Merge the two categories of minimum distance into a new category.

(4) After merging, when the number of categories is equal to 1, go to (5), otherwise calculate the current distances between the new category and the other categories, and then return to (3).

(5) Draw the clustering tree, and then according to the practical requirements and the shape of clustering spectrum diagram, determine the reasonable classification results.

(6) According to the classification results, compose the corresponding IMFs into a high frequency component, a low frequency component and a trend component.

3. Decomposition

3.1. Data

The European Climate Exchange (ECX) located in London, UK, is the largest carbon exchange market within the EU ETS, since its daily carbon trading volume generally accounts for over 80% of the total carbon trading volume of EU ETS. It goes without saying that the ECX can largely reflect the overall state and trends of the EU ETS.

The daily data used is the ECX carbon future price matured in December, 2013, i.e., DEC 13, which is one of the main future contracts currently traded in the carbon market. Fig.1 illustrates DEC13 from April 8, 2008 to June 21, 2013, with a total of 1,335 Transaction day (TD) data points in unit of Euros/ton, which shows that carbon price movements appear to be nonlinear and nonstationary in that the means are changing over time.

Fig. 1. DEC13 from April 8, 2008 to June 21, 2013.

3.2. IMFs

The EMD was implemented in the Matlab R2013a software package produced by the MathWorks Inc, and run on a personal computer with an Intel Core i3-2130 Duo CPU 3.40 GHz and 2.0 GB RAM. Among the abundant Matlab functions library, we have used the *find* and *diff* functions to find out all the local maximal and minimal positions and values of the carbon price, and the *spline* function to form the cubic spline interpolation. In the meantime, the stopping criterion was set as $\alpha = 0.05$, $\theta_1 = 0.05$ and $\theta_2 = 0.5$. Fig. 2 shows that the carbon price is decomposed into eight IMFs plus one residue via EMD. All the IMFs are listed from high to low frequency, and the last one is the residue.

The frequencies and amplitudes of all the IMFs vary over time. As the frequency changes from high to low, the amplitudes of the IMFs are becoming larger: for example, most the amplitudes of IMF1 are smaller than 1, but the amplitudes of IMF8 are limited to 6. The residue slowly varies around the long term mean.

Fig. 2. IMFs and residue for DEC13 derived from EMD.

3.3. IMF statistics

We take some measures to analyze the IMFs: the mean period of each IMF, the correlation between each IMF (residue) and the original carbon price, the variance and variance percentage of each IMF. Table 1 shows related information about this decomposition.

Table 1. Measures of IMFs and residue for DEC13 derived from EMD

	Mean period(TD)	Pearson correlation	Kendall correlation	Variance	Variance as % of the observed	Variance as % of (Σ IMFs +residue)
Observed				50.241		
IMF1	6.51	0.032	0.02	0.038	0.076	0.076
IMF2	14.75	0.023	0.018	0.063	0.125	0.127
IMF3	32.56	0.067*	0.065**	0.104	0.207	0.209
IMF4	76.29	0.102**	0.116**	0.249	0.496	0.500
IMF5	178	0.118**	0.115**	0.509	1.013	1.022
IMF6	534	0.02	0.098**	3.516	6.998	7.062
IMF7	667.5	0.247**	0.045*	1.653	3.290	3.320
IMF8	2670	0.512**	0.290**	10.739	21.375	21.569
Residue	-	0.851**	0.675**	32.918	65.520	66.115
Sum					99.100	100

*: Correlation is significant at the level of 0.05 (2-tailed); **: Correlation is significant at the level of 0.01 (2-tailed).

We define the mean period as the value derived from dividing the number of points by the number of peaks for each IMF, since the frequency of an IMF may change with time continuously and the periods are also not constant. When an IMF is T long and has s peaks, the mean period of such an IMF is T/s . We employ the Pearson product moment correlation coefficient and Kendall rank correlation coefficient to simultaneously

measure the correlations between each IMF (residue) and the observed carbon price. Since these IMFs (residue) are independent of each other, we use the percentage of variance to explain the contribution of each IMF (residue) to the total movement of the observed carbon price. However, due to some limitations [28], the variances of IMFs and residue do not always add up to the total variance, for example, there is a negative 0.9% (99.1%-100%) difference in Table 1.

As shown in Table 1, we can find out that the residue is the dominant mode of the carbon price. Both Pearson and Kendall coefficients, between the residue and the original carbon price, reach a high level of more than 0.851 and 0.675 in Table 1, respectively, both with significance at the level of 0.01. At the same time, the variance of the residue accounts for 66.115% of the total variance. The IMF6, IMF7 and IMF8 are the other important modes with a mean period of more than one year. Meanwhile, the sum of variances for these important components, the IMF6, IMF7, IMF8 and residue, contribute 98.066% of the total variance. On the other hand, the first five IMFs not only exhibit very low correlation coefficients with the original carbon price, but also account for only 1.934% of total variance, which means that these IMFs have no serious effect on carbon price changes.

4. Composition

The hierarchical clustering analysis was also implemented in the Matlab R2013a software package. Among the library of Matlab functions, we have used the *pdist* function to compute the Euclidean distance between pairs of any two IMFs, or any an IMF and the residue; the *linkage* function to create a hierarchical cluster tree using the smallest distance principle; and the *dendrogram* function to generate a dendrogram plot of the hierarchical cluster tree. Fig. 3 gives the clustering results. After careful analysis, the eight IMFs and the residue prefer to be grouped into three categories: (i) the first one: the Euclidean distance is smaller than 6; (ii) the second one: the Euclidean distance lies between 6 and 12; and (iii) the third one: the Euclidean distance is more than 12. Therefore, in terms of the mean periods, the partial reconstruction with IMF1, IMF2, IMF3, IMF4 and IMF5 can be recognized as the high frequency component, the partial reconstruction with IMF6, IMF7 and IMF8 can be treated as the low frequency component, and the residue can be served separately as the trend component. Fig. 4 shows the three components and Table 2 gives statistical measures.

Fig. 3. Hierarchical clustering tree derived from the IMFs and residue.

Each component has its own distinct features. The residue slowly varies around the long term average. Thus, it is considered as the long term trend during the evolution of the carbon price; every sharp up or down of the low frequency component corresponds to a significant trend break, which is an indicator of the effects of a significant trend break; and the high frequency component reflects the effects of short term market fluctuations.

For the movement trend of the observed carbon price, the most important components are low frequency component and trend. Pearson and Kendall correlation coefficients between the low frequency component, trend component and the original carbon price reach 0.572, 0.851, 0.292 and 0.675, respectively, all with significance at the level of 0.01; meanwhile, low frequency components and trends have higher variance contributions, amounting for 27.146% and 70.706%, respectively. The sum of variances for these two important components, low frequency component and trend component, contribute 97.852% of total variance. Meanwhile, the high frequency component has a small effect on the whole changes of the original carbon price.

Fig. 4. Three components of DEC13.

Table 2. Correlation and variance of components for DEC11

	Mean period (TD)	Pearson correlation	Kendall correlation	Variance	Variance as % of the observed	Variance as % of (Σ IMFs +residue)
Observed				50.241		
High frequency component	8.116	0.169**	0.160**	1.000	1.9904	2.148
Low frequency component	445	0.572**	0.292**	12.638	25.155	27.146
Trend	-	0.851**	0.675**	32.918	65.52	70.706
Sum					92.665	100

**: Correlation is significant at the level of 0.05 (2-tailed).

4.1. Trend

The trend has a high correlation with the original carbon price and contributes more than 70% of the total variance of the original carbon price. Therefore, the trend is a crucial factor for the long-term movement of carbon price, and a deterministic force for the carbon price evolution in the long run. The evolution of the trend as a whole is consistent with the economic development in the EU, declaring that the long term trend of the carbon price is determined by EU economic development. The trend appears to decline, which is related to the fact that the global financial crisis since September, 2008, especially the European debt crisis since June, 2011 dragged down the carbon price.

By comparing the trend with the original carbon price, we can find that although the carbon price will fluctuate dramatically due to significant trend breaks, it will return to the trend after the influence of the trend

breaks faded away. For example, the global financial crisis since September, 2008 made carbon price fall suddenly from over 35 Euros/ton to below 15 Euros/ton, but the price rose slowly after that and finally returned to the trend price of about 20 Euros/ton in May, 2009.

4.2. Effects of significant trend breaks

The significant trend breaks such as intergovernmental negotiations, national allocation plans and global financial crisis can seriously affect the carbon price. Because the occurrences of significant trend breaks are not frequently, their effects are mainly embodied in the low frequency component derived from IMF6 to IMF8. In terms of the mean periods of these IMFs, the shortest is about two years and the longest is more than ten years, demonstrating that it is very difficult for the carbon market itself to eliminate these effects soon; a significant trend break can affect the carbon price for a long time. In addition, the amplitudes at some time points could be more than 4 Euros/ton or even higher, showing that the effects of trend breaks on the carbon price can be very serious. Therefore, significant trend breaks can lead to large fluctuations in medium term.

Through separating the effects of significant trend breaks included in the low frequency component from the whole carbon price, we can measure the effect of each significant trend break used as a reference for predicting the effect of the next significant trend break of the same or similar type. For example, during the period of the global financial crisis beginning from September, 2008, carbon price fell to 10 Euros/ton or below from the summit more than 20 Euros/ton in summer, with a decline of over 10 Euros/ton, which roughly means that the maximum effect of this trend break on the carbon price was 10 Euros/ton or above, and the effects of this trend break have continued until present.

4.3. Normal market fluctuations

Besides significant trend breaks and the long-term trend, the carbon price is also influenced by many other factors, such as extreme weather conditions and speculations [1, 3, 4, 9, 12]. Durations of these effects are often short. So they are classified into high frequency trend breaks and their effects are contained in the high frequency component. The IMF1, IMF2, IMF3, IMF4, and IMF5 have shorter mean periods and make little variance contribution, proving that the normal market fluctuations have no serious impact on the carbon price - it is in general less than 2 Euros/ton. However, these trend breaks are becoming more and more frequent and have lately become the fundamental forces of carbon price changes. Thus, normal market fluctuations can be neglected in long-term forecasting, but they are important for short-term forecasting.

In brief, the carbon price is composed of three components: the high frequency component, the low frequency component and the residue. The residue shows the major trend of carbon price in the long-term. The low frequency component expresses the effects of significant trend breaks which have a medium-term impact on carbon price. The high frequency component displays normal market fluctuations which have only a short-term impact on carbon price. Through this method, the carbon price of 30 Euros/ton in August, 2008 can be decomposed into a trend price (about 23 Euros/ton), the effect of a significant trend break (about 8 Euros/ton) and short-term market fluctuations (about -1 Euros/ton); and the carbon price of 8 Euros/ton in August, 2012 can be decomposed into a trend price (about 8 Euros/ton), a significant trend break price (about 0.2 Euros/ton), and a normal fluctuation price (about -0.2 Euros/ton).

5. Conclusions

The contributions of the paper may be summarized as follows. The EU ETS carbon future price of maturity December 2013, e.g. DEC13, is decomposed into eight IMFs and one residue. Through the hierarchical clustering method, three components are identified as (i) short term market fluctuations, (ii) effects of significant trend breaks, and (iii) a long-term trend. The trend slowly changing around the long-term mean can basically determine the evolution of the carbon price in the long-term. Significant trend breaks can trigger the sharp downs or ups in carbon prices in the medium-term. Normal market activities can mainly drive the small carbon price fluctuations in the short-term.

The analyses of these three components of the carbon price can provide us some forecasting strategies: we can firstly predict each component based on its own features, such as applying a polynomial function to fit the trend component, a nonlinear forecasting model such as Support Vector Regression or Artificial Neural Network to simulate low frequency component, and a stochastic model such as ARIMA or GARCH to handle high frequency component, and then integrate their results to obtain a final result. How to forecast them based on their concrete implications and data characteristics will be our future research work.

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