Comparison and Application of Four Multi-scale Decomposition Methods for the Price of Different Carbon Markets

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Abstract. In this paper, EMD, EEMD, CEEMD and MEEMD methods are used to analyze the multi-scale decomposition and application effect of carbon price time series. Through the comparison of indexes, such as orhogonality, completeness and so on, the MEEMD is proved to be the most effective method. MEEMD is used to conduct an empirical analysis of Hubei and EU carbon market. The results show that the biggest impact on the price of Hubei carbon market is the low frequency component, indicating that it is more easily to be interfered by external factors. The most influential factor on the EU carbon market price is the trend component which confirms that the EU carbon market has a strong price discovery function, that is, it has better effectiveness than Hubei carbon market.

Introduction

Price fluctuation reflects the outcome of multi-party games in various market players and is a fundamental way for any market to perform its functions. The more imperfect the market is, the more volatile price fluctuation is and sometimes even causes the market chaos. Therefore, it is very significant to research the carbon price fluctuation. With the initial establishment of China's unified carbon market, it is particularly important to study the fluctuation of carbon price.

Different scholars have studied this issue from many angles. The most common method is time series analysis represented by ARCH type model [1][2][3][4]. Next important to this, some nonlinear models such as Artificial Neural Network are used [5][6][7]. In addition to these, there are other papers on this topic, such as [8].

It can be seen from the above literature review that the biggest problem of the current researches is ignoring the frequency domain, thus fails to fully understand the carbon price fluctuations. This could be solved by an objective data analysis method called EMD. EMD and other signal decomposition methods have made important progress in price fluctuation analysis in recent years, but few scholars compare the characteristics of different methods and their adaptability based on real cases of carbon markets.

In this paper, we will examine four commonly used signal decomposition methods to select the best method suitable for price of carbon market and based on which empirical analysis is made to compare the price fluctuations of Hubei and EU carbon market. Through the empirical analysis, features of the three reconstruction components and the evolution of carbon price are defined and the some suggestions are put forward to reduce the carbon price fluctuation in China.

The Theory and Characteristics of Four Methods

EMD is proposed by Huang et al [9] on the basis of the Hilbert transform. In addition to self-adaptation and high efficiency, the biggest advantage of EMD is solving pseudo-harmonics of Hilbert transform. However, the EMD has a drawback named 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. To solve the mode mixing problem of EMD method, Wu et al. [10] proposed EEMD in 2004. Noise assisted data analysis (NADA) technology is used to add
different white noise to the original time series, thus eliminating and suppressing mode mixing by multiple calculations. However, since the white noise added each time is different, the IMFs and residue of each trial is different, resulting in poor completeness. Yeh et al.[11] proposed the CEEMD method to improve the completeness of EEMD. The difference between EEMD and CEEMD is that a pair of white noise is added to the original signal instead of only a white noise. Thus the decomposition has good completeness. But it is prone to cause pseudo-IMF components. A modified EEMD (MEEMD) was proposed by Zheng Jinde[12] with introducing the permutation entropy(PE) for signal randomness detection. The EMD algorithm is described as following: ① CEEMD decomposition; ② detect whether the decomposed components are abnormal by PE; ③ remove the abnormal components from the original signal; ④ EMD decomposition on the remaining signals to obtain IMFs.

Comparison of Multi-scale Decomposition Methods for Price Fluctuation of Carbon Market

Decomposing Objects and Parameter Design

Taking closing price of Hubei carbon market as the research object, EMD, EEMD, CEEMD and MEMMD methods are used. The total number is 1438 from April 28, 2014 to June 28, 2019. At present, the white noise amplitude and the number of integration should be chosen as 0.1-0.2 times of the standard deviation of the original time series and within 100 respectively. In this paper, the amplitude of white noise is chosen as 0.2 times and the number of integration is 100. Figure 1 shows the decomposition results of EMD, EEMD, CEEMD and MEEMD.

![Figure 1. Decomposition results of four methods.](image)

Evaluation Index and Its Significance

The orthogonality, completeness, number of IMFs and calculation time are used to evaluate the decomposition effects of four methods. (1) Orthogonality: it is implied to express the non-
dependence or decoupling among the decomposed signals. It reflects the important characteristic whether the signal information is lost or the signal components are overlapped in the process of original signal decomposition. (2) Completeness: Completeness is indicated the consistency of signal before and after decomposition. If the error between the reconstructed signal and the original signal is very small, then we consider that the completeness of the reconstructed signal is good. (3) Number of IMFS components: Number of IMFS components reflect whether there are redundant components after decomposition which is also known as pseudo components that interfere with actual components.

Comparison of Four Methods

Table 1 gives the calculation of the evaluation index of each method. From Table 1, we can come to the following conclusions:

1. The smallest orthogonal calculation is obtained by MEEMD which indicates that MEEMD has the least signal information loss and mode mixing.
2. The complete calculations obtained by CEEMD and MEEMD are not much different and better than the results obtained by the other two methods indicating the decomposition error is suppressed more effectively by CEEMD and MEEMD.
3. The number of IMFS component decomposed by MEEMD is the least which means by using MEEMD, the interference of pseudo component can be avoided effectively.

To sum up, MEEMD method has significant comprehensive advantages.

| Methods | Computing time(s) | Orthogonality | Completeness | Number of IMFS |
|---------|-------------------|---------------|--------------|----------------|
| EMD     | 0.7031            | 0.0281        | 489.4094     | 7              |
| EEMD    | 4.4534            | 0.0465        | 508.4389     | 7              |
| CEEMD   | 4.4803            | 0.0181        | 519.6091     | 10             |
| MEEMD   | 4.4821            | 0.0064        | 517.3839     | 6              |

Comparison of Price Volatility Analysis of Hubei and EU Carbon Market Based on MEEMD

The closing price of Hubei and EU carbon markets are chosen as the research objects in this paper. MEEMD method is used for decomposition, index calculation and reconstruction.

Price Volatility Analysis of EU Carbon Market Based on MEEMD

The EU carbon market has developed the biggest and most perfect carbon market in the world. The daily closing price from January 1, 2013 to June 28, 2019 has been selected, 1663 data totally. The MEEMD method is used and the decomposition results are shown in Figure 2 below.
Calculation and Analysis of Relevant Indexes

The IMFs and trend components of Hubei and EU carbon markets are analyzed based on three indexes of average period, Pearson correlation coefficient and variance contribution rate. The statistical results of price component index of Hubei and EU carbon market are shown in Table 2.

Table 2. Price component index of Hubei and EU carbon market

|                | Hubei carbon market | EU carbon market |
|----------------|---------------------|------------------|
| IMFs           | Avg. period | Pearson | Variance | Contribution rate (%) | IMFs | Avg. period | Pearson | Variance | Contribution rate (%) |
| IMF1           | 15.8        | 0.0809   | 0.38     | 1.49       | IMF1 | 15.99       | 0.0499   | 0.0736   | 0.1769       |
| IMF2           | 27.1        | 0.1418   | 0.48     | 1.89       | IMF2 | 31.98       | 0.0856   | 0.0739   | 0.1777       |
| IMF3           | 49.6        | 0.1896   | 2.03     | 7.99       | IMF3 | 75.59       | 0.0596   | 0.4160   | 1.0004       |
| IMF4           | 119.8       | 0.6657   | 1.41     | 5.55       | IMF4 | 184.77      | 0.0804   | 0.2604   | 0.0626       |
| IMF5           | 359.5       | 0.5878   | 3.58     | 14.08      | IMF5 | 554.33      | 0.1037   | 0.9334   | 2.2445       |
| IMF6           | 1438        | 0.8575   | 13.47    | 52.99      | IMF6 | 1663        | 0.2890   | 12.1201  | 29.1458      |
| Trend          | —           | 0.2772   | 4.07     | 16.01      | Trend | —          | 0.8025   | 28.6577  | 67.6217      |
| Total          | 25.42       | 100      |          |            | Total | 42.5351     | 100      |          |              |

It can be seen from Table 2 that the average period is gradually increasing. Variance contribution rate of IMF5, IMF6 and trend component are much higher than that of other components and the corresponding Pearson Correlation Coefficient are also larger than others’, indicating the components have a larger correlation and influences with the original time series.

Reconstruction of IMFs Component

In order to make each IMF components have a clear physical meaning, it is necessary to reconstruct the decomposed IMFS components. Through reconstruction, the new high frequency and new low frequency component are generated. In this paper, we use t-test to identify for which (i) the mean significantly departs from zero proposed by Zhang [13] in 2008. Once (i) is identified as a significant change point, partial reconstruction with IMFs from this to the end, is identified as the low frequency component and the partial reconstruction with other IMFs is identified as the high frequency component. The t-test of IMFS components are shown in Table 3.

Table 3. T-test of IMFs component of Hubei and EU carbon market

|                | Hubei carbon market | EU carbon market |
|----------------|---------------------|------------------|
| IMFs           | Mean | Standard deviation | T value | IMFs | Mean | Standard deviation | T value |
| IMF1           | -0.0065 | 0.5692           | -0.433 | IMF1 | -0.0016 | 0.2994           | 0.2179 |
| IMF2           | -0.0082 | 0.6011           | -0.5172 | IMF2 | 0.0021  | 0.3128           | 0.2738 |
| IMF3           | 0.0111 | 0.5873           | 0.7167 | IMF3 | 0.0080  | 0.6255           | 0.5216 |
| IMF4           | 0.1135 | 1.8384           | 2.3411 | IMF4 | -0.0205 | 0.5585           | 1.4968 |
| IMF5           | 0.1999 | 0.9475           | 8.000 | IMF5 | 0.0832  | 0.9502           | 3.5707 |
| IMF6           | 0.1545 | 2.2566           | 2.5962 | IMF6 | 0.0037  | 1.9553           | 0.0772 |

From the results of Table 3, it can be seen that the mean significantly departs from zero when i is 4. Therefore, add IMF1 to IMF3 to form a new high frequency component, add IMF4 to IMF6 to form a new low frequency component and the residue is taken as a trend component.

Index of Reconstruction

The high frequency and low frequency component after reconstruction of Hubei and EU carbon markets are shown in Figure 3 and figure 4.
To analyze the characteristics of above components, calculation of each index is carried out and results are shown in Table 4.

Table 4. Index of components after reconstruction of Hubei and EU carbon market.

| Component       | Hubei carbon market | EU carbon market |
|-----------------|---------------------|------------------|
|                 | Avg. period | Pearson | Variance | Contribution rate (%) | Avg. period | Pearson | Variance | Contribution rate (%) |
| High frequency  | 20.54       | 0.10    | 3.98     | 15.71   | 17.14       | 0.13    | 0.83     | 1.80       |
| Low frequency   | 59.92       | 0.95    | 17.29    | 68.23   | 83.15       | 0.50    | 16.55    | 35.95      |
| Trend(RS)       | —           | 0.28    | 4.07     | 16.06   | —           | 0.80    | 28.66    | 62.25      |
| Total           | 1.33        | 25.34   | 100      | 100     | 46.04       | 100     |

It can be seen from Table 4, for Hubei carbon market, the low frequency component has the greatest impact while high frequency and Trend component have almost the same impact about 15%, while the situation of EU carbon market is quite different. The trend component has the greatest impact on carbon price, followed by the low-frequency component while the high frequency component has little impact on the carbon price which is less than 2% that means its influence is almost negligible.

The Influence of Different Component on the Carbon Price Fluctuation

The impact of different components on price fluctuation of Hubei and EU carbon market is analyzed as follows.

The high-frequency component is due to the short-term supply and demand imbalance of the market. For Hubei carbon market, high-frequency component has a certain impact, while for EU carbon market, the high frequency component has little impact on the long-term price but it has an impact on short-term price fluctuations.
The low-frequency component reflects the mid-term fluctuations in carbon prices, indicating the impact of macroeconomic conditions, major economic and political events. The impact of low frequency component is very different in the price fluctuations of Hubei and EU carbon markets. For Hubei market, the low frequency component is the dominant factor of price fluctuations, that is, it is more likely to be interfered by external factors, resulting in poor market effectiveness.

The trend component reflects the long-term trend of carbon price, indicating the degree to which the internal mechanism of carbon market. It is formed by a comprehensive game of all stakeholders involved in carbon market transactions in the world. When new changes are generated, price can be self-adjusted through the market mechanism to reach equilibrium prices again. The larger the proportion of the trend component is, the more powerful price discovery function is. The correlation of the Hubei carbon market is relatively small and that of EU market is very large. The trend component is the most important reason affecting the EU carbon price while that has a much smaller impact on Hubei carbon price. It reflects the price discovery function of carbon market in China is relatively weak compared with mature carbon market which means there is still a long way to build a healthy and stable unified carbon market in China.

Suggestions

To better build China's unified carbon market, three following suggestions are proposed:

Strengthen capacities of predicting major events. It is necessary to improve the emergency response capability of China's carbon market price to external shocks. In particular, the establishment of a unified carbon market is to better integrate into international carbon trading system. If there is no ability to withstand major events, then China's carbon market will face greater risks.

Reducing government intervention. It can be seen from the above analysis that the price discovery function of China's carbon market is far weaker than the EU carbon market. It is known the better the liquidity is the stronger price discovery function is which helps the long-term healthy development of the carbon market.

Building perfect trading framework and system. It is necessary to learn the perfect trading framework and system that the EU carbon trading market has already established, thus giving full play to the rational and effective allocation of resources by the market mechanism.

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