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Disentangling the drivers of carbon prices in China's ETS pilots — An EEMD approach☆

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ABSTRACT

Excessive price fluctuations would affect the effectiveness of Emission Trading Scheme (ETS) and low-carbon investment. Therefore, the drivers of carbon prices need to be disentangled to analyze the price formation process, which is important for both policy makers and investors. By applying the Ensemble Empirical Mode Decomposition (EEMD) method, we decompose the historical carbon price data of the five ETS pilots in China into five groups of the independent Intrinsic Mode Function (IMF) sequences and the residue, respectively. Then, the IMFs and the residue in each pilot are reconstructed into a high frequency component, a low frequency component and a trend component, thus disentangling the effects of short-term market fluctuations, significant events, and the long-term trend. The main findings are as follows. First, the IMF with a period around one year is the most influential factor, which reflects that pilots are characterized by the yearly cycle. Second, significant events have greater impacts than short-term market fluctuations, and are the dominant driver in Shanghai and Beijing pilots. Third, the long-term trend plays a decisive role in Shenzhen, Guangdong and Hubei pilots. The price stabilization mechanism is critical to avoid a severe imbalance between demand and supply in the long run.

1. Introduction

As the world's largest greenhouse gas emitter, China has demonstrated its determination to tackle climate change. In June 2015, China submitted its Intended Nationally Determined Contribution, proposing the target of reducing carbon intensity by 60 to 65% below 2005 levels by 2030 and peaking its CO_2 emissions around 2030. The post-2020 commitment signals a reinforced intention for climate change mitigation and adaptation. To achieve these targets effectively, China has regarded ETS as the "flagship" policy to lower carbon emission. Seven ETS pilots have come to operation since 2013 to gain experiences, covering Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Hubei, and Guangdong. China announced the official launch of a national ETS in December 2017.

ETS creates a price mechanism for carbon emissions, which serves as leverage for optimally allocating a certain quantity of allowance among emitters. In the short run, the carbon price provides the incentive for covered enterprises to reduce emissions cost-effectively. In the long term, these enterprises would incorporate carbon prices into their long-term investment decisions, stimulating clean technology development and market innovation. To sum up, the carbon price plays a significant role in the carbon ETS and low-carbon economy. Robust and persistent carbon price would ensure the transition from a carbon-intensive economy to a low-carbon one. However, the experiences show that ETS may be under the risk of frequent price fluctuations, which can be observed in EU ETS (Convery et al., 2008; Zhang and Wei, 2010). As indicated in Fig. 1, China ETS pilots have yielded different carbon prices, and some pilots have also witnessed dramatic price changes.

The carbon price is affected by various factors, including market power, institutional design, energy prices, etc. These factors contribute to shaping price sequences with different duration, amplitude and frequency. Market power and speculation occur at a high frequency in ETS, and may cause the short-term fluctuations of carbon price (Hintermann, 2010). Regulatory events, such as allowance allocation, trading rules, offset mechanism and intertemporal banking, can cause sharp price fluctuations with long duration (Alberola and Chevallier,

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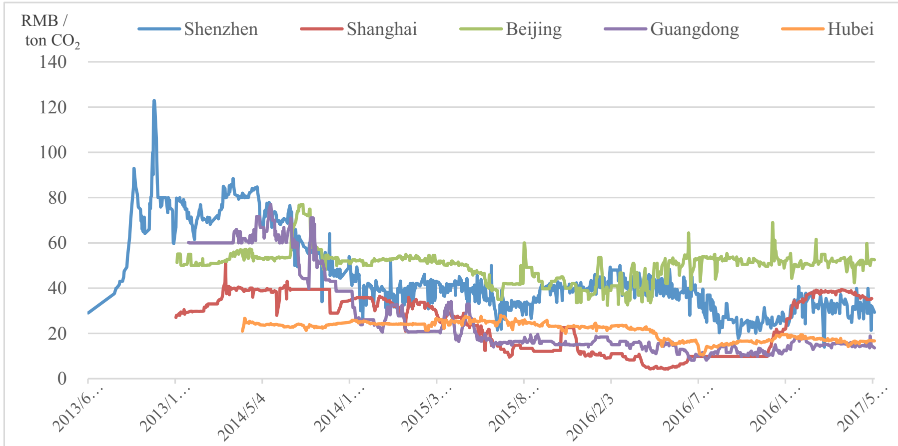

Fig. 1. Carbon prices of 5 China's ETS pilots.
Data source: The carbon price data is collected from the official website of each ETS pilot.

2009; Chevallier, 2009; Song et al., 2018). The decisions regarding total allowance would substantially impact the carbon price, even lead to extreme price fluctuations (Benz and Trück, 2009; Creti et al., 2012). Energy prices may significantly affect allowance prices depending on the market structure of energy (Aatola et al., 2013; Ji et al., 2018; Kanamura, 2016). The impacts of different energy prices are inconsistent and would change with time (Fan and Todorova, 2017; Hammoudeh et al., 2015). In addition, the long-term evolution of the carbon price is proven to be greatly driven by the macroeconomic growth (Chevallier, 2011; Feng et al., 2011; Koch et al., 2014). As the drivers are superimposed onto each other simultaneously, carbon price signals are considered as the integration of different sequences. Thus, in order to analyze the price formation process, it is necessary to decompose carbon prices and study different types of drivers.

Wide-ranged fluctuations have triggered a political debate on whether and how regulators should engage in stabilizing carbon prices. Under ideal conditions, the cap will be achieved at least cost if no regulatory intervention occurs. However, market participants encounter uncertainties beyond what a social planner faces (Salant, 2016). An increasing body of literature argues that price stabilization mechanisms should be established, because it's hard for ETS itself to response to all shocks (Ellerman et al., 2015; Grosjean et al., 2016). Many measures have been proposed to stabilize carbon prices, such as price floors in RGGI and Market Stability Reserve (MSR) in EU ETS. There are also different views: critics warry that regulatory events account for the existence and timing of price jumps in the EU ETS (Holt and Shobe, 2016; Perino and Willner, 2016); supporters argue that an ETS with MSR has lower price variation and lower expected abatement costs (Fell, 2016; Kollenberg and Taschini, 2016). The core of this debate lies in how regulatory events and market fundamentals influence carbon prices. This calls for disentangling the effects of short-term market fluctuations, significant events and long-term trend.

Therefore, this study decomposes carbon prices in China's ETS pilots into a group of sequences from high to low frequency by applying the EEMD method. Then the study reconstructs high frequency component, low frequency component and trend component, which correspond to short-term market fluctuations, significant events and long-term trend respectively. The contributions of this study are twofold. First, it gains a deeper understanding of formation mechanism of carbon prices by disentangling the drivers of carbon prices. Comparisons are made among those drivers in five ETS pilots to find the rule of carbon price fluctuations. Second, it explores the effects of short-term market fluctuations, significant events and long-term trend. This will facilitate proper valuation of price stabilization mechanisms and assist regulator to develop appropriate policies.

The remainder of the paper is organized as follows. Section 2 reviews the methodologies applied in the literature. Section 3 details the EEMD approach and the data. Section 4 presents the results and analysis. Section 5 further studies three types of factors respectively. Section 6 draws conclusion.

2. Literature review

Different econometric approaches have been adopted to study the carbon price and its influencing factors.

The common methods adopted in the literature are financial econometric techniques, such as Generalized Auto Regressive Conditional Heteroscedasticity (GARCH), Vector Auto Regression (VAR) and Vector Error Correction Models (VECM). GARCH models can capture the stylized facts including clustering effects and asymmetric leverage effects, hence they are broadly employed to depict carbon price dynamics (Benschopa and López Cabreraa, 2014; Benz and Trück, 2009; Deeney et al., 2016; Paolella and Taschini, 2008). By extending the univariate framework of autoregressive process to a multivariate setting, VAR models are adopted to address the interactive relationship among the carbon price and its fundamentals (Arouri et al., 2012; Tan and Wang, 2017; Zeng et al., 2017). When applied to nonstationary time series, VECM models perform better to avoid risk of spurious regressions and loss of important long-run information (Chevallier, 2012; Creti et al., 2012; Freitas and Silva, 2013). To endogenize the time-changing influences caused by structural breaks, regime-switching models are introduced to provide a better in-sample fit by distinguishing different states of the data (Lutz et al., 2013; Segnon et al., 2017). In addition, the event study approach is recently applied to provide a detailed description of the policy impact on carbon prices (Fan et al., 2017; Song et al., 2018).

Another branch to study financial prices is the trend–cycle decomposition methods. Since financial prices are often regarded as the superposition of different sequences, decomposition methods have been proposed in the economic or financial series analysis to unveil the temporal characteristics and driving forces of the economic fluctuations. There are two main types for the trend–cycle decomposition approaches, the model-based methods and non-model-based ones. One commonly used model-based approach is the BN decomposition method under the hypothesis that the trend and cyclical term are subject to a certain pattern (Beveridge and Nelson, 1981). The BN method decomposes the economic series into a permanent trend component which contains the effect of persistent factors, and a stationary cyclical component with zero mean which reflects the influence of transitory factors. The BN method has been continuously improved and used in the economic series decomposition and business cycle analysis (Balcilar et al., 2017; Kim, 2008; Murasawa, 2015; Narayan and Thuraisamy, 2013). The non-model-based methods include HP filter, Band-pass filter, Wavelets etc., among which the most popular is HP filter (Chen and Reeves, 2012; Grant and Chan, 2017; He et al., 2013; Lisi and Nan, 2014; Wang et al., 2017). The HP filter does not specify the model that trend term and the cyclical component should conform, but it requires that the trend should meet a certain smoothness (the λ parameter), thus isolating the series components of interest.

Due to a short operation time and frequent policy adjustments, ETS pilots in China are characterized by poor data quality. The financial econometric techniques may not be appropriate to portray these carbon prices. Besides, those methods lack economic meaning and cannot explain the inner driving forces that move carbon prices (Feng et al., 2011). The event study method only focuses on the external impact of major events and cannot inspect the influence of short-term market fluctuations and long-term trend. As for trend–cycle decomposition methods, the BN decomposition method assumes that the trend and cyclical component are related, so the influence of different factors on the economic sequence cannot be completely separated. Furthermore, the limitation of HP filter is the prior specification of λ which would greatly affect the cycle estimation (Maravall and del Río, 2007).

The EEMD approach is a more suitable method and could fill the gap mentioned above. Compared to financial econometric techniques, the EEMD approach has no requirement on linearity and stability of data, thus applying well to the poor data quality in China's ETS pilots. The method can also solve the dilemma between the difficulties in modeling and the lack of economic implications (Zhu et al., 2015). Relative to the BN method, EEMD can decompose the original price into a series of independent sequences and a residue, thus distinguishing the effects of different influencing factors. In contrast with non-model-based decomposition methods, EEMD could realize decomposition according to the local characteristics of the original series. In view of these advantages, the EEMD method has been widely used in the literature of price changes and forecasting, like crude oil prices (Jianwei et al., 2017; Yu et al., 2016), stock prices (Xu et al., 2016; Zhang et al., 2017), and gold prices (Ming et al., 2016; Xian et al., 2016) etc. Therefore, we adopt the EEMD approach to disentangle the different drivers of carbon prices in China's ETS pilots.

3. Method and data

3.1. Ensemble empirical mode decomposition

The EEMD approach is an improved algorithm of Empirical Mode Decomposition (EMD). The EMD method can decompose the data adaptively and completely without prior processing of the original sequence (Huang et al., 1998). The decomposition should satisfy two conditions: first, all IMFs have the same number of extrema and zero-crossings (difference does not exceed 1); second, the IMF is axially symmetric with zero mean to ensure that it is a periodic function with a zero-mean value. The calculation steps are as follows.

1) Confirm all maximum and minimum values of the time series $z(t)$; use the cubic spline interpolation function to give the upper and lower envelopes $e_{upper}(t)$ and $e_{lower}(t)$; and calculate mean $m(t)$ of the upper and lower envelopes:

$$m(t) = (e_{upper}(t) + e_{lower}(t))/2 \tag{1}$$

2) Separate the mean value from the time series and define the difference with the original sequence as $d(t)$:

$$d(t) = z(t) - m(t) \tag{2}$$

3) Treat $d(t)$ as a new $z(t)$ if $d(t)$ does not meet the IMF's conditions and repeat the above steps until the above two requirements are met, then define it as the IMF_i and express as $f_i(t)$ to separate from $z(t)$ and obtain a new residue $r_i(t)$:

$$r_i(t) = z(t) - f_i(t) \tag{3}$$

4) Repeat the above steps until the stopping criteria is met to obtain the nth residue[1]:

$$r_n(t) = r_{n-1}(t) - f_n(t) \tag{4}$$

Finally, the IMF component can be expressed as follows:

$$z(t) = \sum_{i=1}^{n} f_i(t) + r_n(t) \tag{5}$$

However, the EMD suffers from mode-mixing problem which can be illustrated as some fast-intermittent signals riding on a slow-oscillating wave (Shen et al., 2014). The EEMD method is proposed to overcome this drawback, by adding white noise to the original sequence to ensure the separation of real signal sequence (Wu and Huang, 2004). The steps are as below:

1) Add a white noise sequence to the original, which meets the following condition:

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \tag{6}$$

where N is the number of integrations, ε and ε_n are white noise amplitude and the final standard deviation of error, respectively;

2) Decompose the synthesized sequence into the IMFs in a similar way to EMD;

3) Repeat the above steps, take a different white noise sequence each time, and select the corresponding IMF's mean value as the final IMF sequence, $f_i(t)$.

3.2. Fine-to-coarse reconstruction

The effects of various drivers are included in the group of independent IMFs and the final residue $r(t)$. According to the features of frequency, duration and amplitude, these IMFs can be divided into several categories to deeply understand different types of drivers. We reconstruct the IMFs and the residue into high frequency component, low frequency component and trend component by the fine-to-coarse reconstruction algorithm. Procedure is as followed.

1) Calculate the sum of the superposition sequences from $f_1(t)$ to $f_i(t)$ and the mean value $\overline{f_i}$;

2) Identify IMF_1 to IMF_{i-1} as high frequency IMFs, if $\overline{f_i}$ significantly deviates from zero by conducting t-test, while the rest IMFs as low frequency IMFs.

3) Define the sum of all high frequency IMFs as the high frequency component, the sum of all low frequency IMFs as the low frequency component, and the residual $r(t)$ as the trend component.

The three components correspond to the effects of short-term market fluctuations, significant events and long-term trend. Each component has its own distinct characteristics, and is interpreted in line with its time scale and fluctuant feature:

First, the high frequency component (HFC) has shorter period and forms fast oscillation around zero mean. It represents the effects of short-term fluctuations in the carbon ETS caused by market power, market psychology and speculative behavior, etc. The occurrence of these factors is frequent, while their impacts usually last for a short time. Their effects are contained in the high frequency component with short duration and narrow amplitude.

Second, the low frequency component (LFC) has longer period and larger amplitude, and gradually falls back to zero when the influence fades. It reflects the impact of significant events on the carbon price, including regulation adjustments, information disclosure, international politics and negotiations, etc. These events occur at a low frequency,

[1] The stopping criteria is proposed by Huang et al. (2003): the component $f_i(t)$ or the residue $r(t)$ becomes so small that it is less than the predetermined value of a substantial consequence; or the residue $r(t)$ becomes a monotonic function which no more IMFs can be extracted.

but their influences are great and long.

Third, the trend component (TC) shows a long-term slow and smooth change, depicting the trend evolution of the original carbon price. It is determined by the overall demand and supply of allowances in the long run, implying the influence of factors such as macroeconomic growth and energy prices from the demand side, and allocation plan and related price stabilization mechanism from the supply side.

3.3. Data

The main challenge in studying China's ETS pilots is the large number of zero trading volume. To ensure meaningful conclusions, the study focus on five China's ETS pilots, including Shenzhen, Shanghai, Beijing, Guangdong and Hubei. The two remain pilots, Tianjin and Chongqing are excluded due to poor data availability in both pilots. And we adopt the average carbon price which is defined as the ratio of daily transaction value to daily trading volume of allowances. The carbon price data is collected from the official website of each ETS pilot covering the period from the launching time of each pilot to May 31, 2017.

4. Empirical analysis

4.1. Decomposition

Table 1 shows the decomposition results of five ETS pilots by EEMD, including average period, variance ratio and IMF's frequency identification. Variance ratio can be used to evaluate the relative contribution of each IMF to the overall carbon price, because the IMFs separated from the original price are mutually independent.

First, the average period and variance ratio of the IMFs vary over time. High frequency IMFs exhibit short duration and relatively weak impact; while low frequency IMFs show longer duration and stronger influence. The average periods of high frequency IMFs are mostly under 33 days, and the effects from these short-term factors are weak with the variance ratios mostly below 5%. The low frequency IMFs usually last from two weeks to more than one year, and make larger contributions to carbon prices with obvious higher variance ratios.

Second, the IMF with a period around one year (i.e. IMF7) presents relatively higher variance ratios in five pilots, implying that ETS pilots are characterized by the yearly cycle. It is because the ETS pilots are based on the annual cycle design, including allowance allocation, compliance, measurement, reporting and verification (MRV) process, etc. Only in Guangdong pilot, the most influential sequence is IMF6 with a period of 111 days. It may be related to its periodical auction regulation, hence the three-month factor presents a higher impact.

Third, most pilots have 4 high frequency IMFs and 4 low frequency IMFs, while Shenzhen pilot has 2 high frequency IMFs and 6 low frequency IMFs. This may be due to the frequent regulation adjustment especially the trading rules changes in Shenzhen, resulting in the shorter periods of low frequency IMFs.

4.2. Reconstruction

The high and low frequency IMFs are added respectively to get HFC and LFC of the carbon price in each pilot. Fig. 2 takes Shenzhen ETS pilot as an example to plot the line graph of three components and original carbon price. Consistent with the theoretical expectation, HFC forms fast oscillation around zero mean, LFC shows similar amplitude with carbon price, and original price moves around TC in the long run. The graphs of other four pilots present the same feature.

Table 2 provides the variance ratios and Pearson correlation coefficients of HFCs, LFCs and TCs. The IMFs are mutually independent, so are the three components. Therefore, variance ratio can be used to evaluate the relative contribution of each component to the overall carbon price. Pearson correlation coefficient measures the direction and strength of a linear correlation between two random variables. The positive sign indicates a positive correlation and greater absolute value means higher degree of the correlation. It's generally assumed that a coefficient value greater than 0.4 signifies an above-medium correlation.

First, significant events have much greater impacts on the carbon price than short-term market fluctuations in all five pilots. According to Table 2, the variance ratios of LFCs are obviously higher than those of HFCs, which implies that the significant events explain a much larger proportion of carbon prices. In addition, the Pearson correlation coefficients of LFCs are all significant at 1% level, and reach a high level of above 0.6 except Guangdong. The obvious higher coefficients also indicate a closer correlation between significant events and carbon prices.

Second, the significant events are the dominant driving force of carbon prices in Shanghai and Beijing pilots. Both pilots have changed the allocation plans and total caps to a large extent, hence making profound influences on the carbon prices. Especially in Shanghai pilot, the allowance allocation period has been altered from three years to one year. The finding is consistent with that of Song et al. (2018), which reveals that carbon policies are the main driver of carbon prices rather than the fundamentals of supply and demand in Shanghai pilot.

Third, the long-term trend plays a decisive role in Shenzhen, Guangdong and Hubei pilots. The variance ratios of TCs in those pilots are more than 60%, and the Pearson correlation coefficients are all higher than 0.8. It implies that the most influential factor is the long-

Table 1
IMF statistics and frequency identification of five pilots.

		IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
Shenzhen	Average period (day)	3.06	7.08	14.49	26.85	60.87	182.6	304.33	456.5
	Variance ratio	1.91%	1.10%	3.60%	2.82%	2.37%	5.34%	10.88%	0.97%
	Frequency identification	HF	HF	LF	LF	LF	LF	LF	LF
Shanghai	Average period (day)	3.21	6.78	15.74	33.36	69.5	119.14	417	834
	Variance ratio	0.22%	0.22%	0.24%	0.61%	2.40%	2.45%	70.90%	1.68%
	Frequency identification	HF	HF	HF	HF	LF	LF	LF	LF
Beijing	Average period (day)	3.27	7.63	14.21	32.96	82.4	206	412	824
	Variance ratio	4.36%	3.07%	3.80%	5.93%	9.64%	10.41%	49.98%	1.90%
	Frequency identification	HF	HF	HF	HF	LF	LF	LF	LF
Guangdong	Average period (day)	3.04	7.35	14.98	29.96	77.9	111.29	389.5	779
	Variance ratio	0.25%	0.19%	0.77%	0.53%	0.98%	2.84%	1.43%	1.27%
	Frequency identification	HF	HF	HF	HF	LF	LF	LF	LF
Hubei	Average period (day)	3.25	7.13	15.4	32.08	59.23	192.5	385	770
	Variance ratio	0.70%	0.45%	0.96%	0.98%	1.55%	14.11%	15.74%	0.25%
	Frequency identification	HF	HF	HF	HF	LF	LF	LF	LF

Note: The average period is defined as the value derived from dividing the number of points by the number of peaks for each IMF. The variance ratio is the percentage of a IMF's variance to the total variance of the IMFs and the residual. HF denotes high frequency IMF, while LF is low frequency IMF.

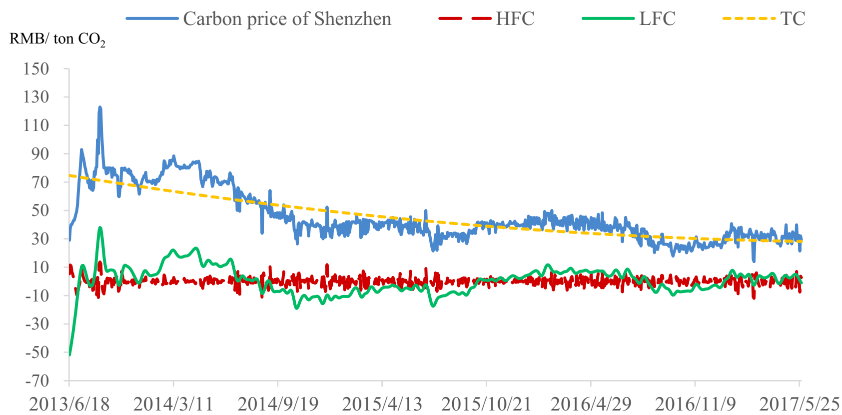

Fig. 2. Carbon price, high frequency component, low frequency component and trend component of Shenzhen pilot.
Note: HFC, LFC and TC denote the high frequency component, the low frequency component and trend component, respectively.

Table 2
Variance ratios and Pearson correlation coefficients of three components in five pilots.

ETS pilots	High frequency component		Low frequency component		Trend component	
	Variance ratio	Pearson correlation coefficient	Variance ratio	Pearson correlation coefficient	Variance ratio	Pearson correlation coefficient
Shenzhen	3.27%	0.17***	31.59%	0.65***	65.14%	0.84***
Shanghai	1.34%	0.16***	82.19%	0.89***	16.48%	0.07***
Beijing	20.94%	0.47***	68.93%	0.84***	10.13%	0.38***
Guangdong	2.59%	0.18***	9.41%	0.27***	87.99%	0.93***
Hubei	4.56%	0.20***	31.85%	0.66***	63.60%	0.83***

Note: * means a significant correlation in the 0.10 level (bilateral); ** means a significant correlation in the 0.05 level (bilateral); *** means a significant correlation in the 0.01 level (bilateral). The variance ratio is the relative variance ratio, i.e., the percentage of a component's variance to the total variance of the three components.

term supply and demand structure, of which the effect is difficult to be eliminated soon for the carbon market itself.

5. Disentanglement and discussions

To further study the impacts of three components respectively, a horizontal comparison of each component is then made among five pilots.

5.1. The impact of short-term market fluctuations

From the comparison of HFCs' line graph in Fig. 3, we have the following findings.

First, the effects of HFCs are usually within 15 RMB/ton of CO_2, while that of Hubei is below 5 RMB/ton of CO_2. Hubei has proposed a set of price stabilization mechanism, so the carbon price has been relatively stable even with largest trading volume.

Second, the HFC in Shenzhen pilot is always frequent and violent. Carbon prices of Shenzhen pilot frequently reaches price limits,[2] which indicates that the pilot may exist serious speculative behavior. Ren and Lo (2017) also finds that there are significant fluctuations and excessively high kurtosis in trading volume of Shenzhen pilot.

Third, HFCs have higher frequencies and amplitudes in the initial stage and slow down gradually in Shanghai and Guangdong pilots. This suggests that the impact of short-term market fluctuations on carbon prices is decreasing with increasing experience, which shows a learning effect in these pilots.

5.2. The impact of significant events

The comparison of LFCs among five pilots is graphed in Fig. 4. It can be found that the ups and downs of the LFCs usually correspond to the time when external event occurs.

First, the amplitudes of LFCs are generally less than 50 RMB/ton of CO_2, significantly higher than those of HFCs. It suggests that carbon market is highly sensitive to shocks from significant events. Different pilots show divergence on the LFCs' amplitudes, with up to 50 RMB/ton of CO_2 in Shenzhen, 15-25 RMB/ton of CO_2 in Shanghai, Beijing and Guangdong pilots and 7 RMB/ton of CO_2 in Hubei pilot.

Second, the frequencies of LFCs are low in all pilots except Shenzhen. This may be due to its high frequency in policy adjustments and trading rule changes in Shenzhen pilot. It experienced 9 times of policy adjustments and 6 times of trading rules changes in the sample period.[3]

Third, the sources of external shocks are complex and multifaceted. The regulation adjustments are the main source of significant events in the pilot markets, and some cases are presented in Fig. 4. China's ETS pilots are still in the early stage, and the authorities often adjust regulations, such as coverage, allowance auction, and offset mechanism. On the one hand, these adjustments may improve the market mechanism, while on the other hand, they can also cause sharp fluctuations in carbon prices.

5.3. The impact of long-term trend

Fig. 5 depicts the trend curve of each pilot which slowly varies around the long-term average. The trajectory of trend component

[2] Shenzhen guards against both highs and lows, and limits price fluctuations to no more than 10% per day.

[3] The Statistical data of policy adjustments and trading rule changes are derived from the official website of China Emissions Exchange in Shenzhen, collected and collated by the author. The website is: http://www.cerx.cn/en/.

Fig. 3. High frequency components of five pilots.

mainly reflects the long-term supply and demand structure of allowance. The rising trend curve suggests that the demand for allowance exceeds the supply; the declined curve refers to a surplus of allowance; and the smooth curve discloses a relative balance of supply-demand structure. By comparing the trend with the original carbon price, it can be found that the trend is consistent with the evolution of carbon prices in the long run.

First, the trend curves of Shenzhen and Guangdong pilots gradually stabilize after a sharp decline. As the first ETS pilot launched in China, the initial price of Shenzhen pilot was rather high due to the speculative behavior and information asymmetry. The price trend declined rapidly with the constant disclosure of market information, and gradually stabilized when Shenzhen took the ex-post adjustment on firm-level allowances.[4] Guangdong pilot auctioned 3% of allowances and set a reserve price of 60 RMB/ton of CO_2 at the beginning. Nevertheless, the loose cap and cancelation of price floor caused the sharp fall of carbon prices. The price trend of Guangdong rebounded by increasing the auction proportion and tightening the cap.[5]

Second, the trend curve of Shanghai shows a “U” type of first descending slowly and then rising greatly. Shanghai pilot issued free allowances of three years in its first stage (2013–2015),[6] resulting in a surplus of allowance and a decline of trend curve. In 2016, Shanghai adjusted its allowance allocation plan and tightened free allowances for some covered industries. As a result, the supply-demand structure started to reverse, and the trend curve went upward obviously.

Third, the trend curves of Hubei and Beijing pilots are relatively stable, indicating the relative balance of supply-demand structure. This may be due to a set of price stabilization mechanisms. Beijing pilot implements a strict price limit with a clear corridor of 20–150 RMB/ton of CO_2,[7] and related allowances auction and buy-back mechanism. Hubei pilot sets up a systematic carbon price stabilization mechanism, including allowance reserve, allowance automatic cancelation, ex-post adjustment and price limit. Therefore, their trend curves are relatively stable in the whole sample period.

In conclusion, the long-term trend of carbon prices mainly relies on the demand side factors such as macroeconomic growth,[8] and the supply side factors including allocation plan and the stabilization mechanism. To avoid a severe imbalance between demand and supply of allowances, attention should be paid on carbon price stabilization mechanism.

6. Conclusions

This paper decomposes the carbon price data of five ETS pilots in China by applying the EEMD approach. And then, it disentangles the

[4] See the Notice of Shenzhen Development and Reform Committees (DRC) on the Implementation of ETS in 2016.

[5] See the Notice of Guangdong DRC on Allowances Allocation Measures in 2016.

[6] See the Notice of Shanghai DRC on Allowances Allocation and Management Measures in 2013–2015.

[7] See the Notice of Beijing DRC on Open Market Operations Management Measures in 2014.

[8] Energy prices have been proven of non-significant correlation with carbon prices in china's ETS pilots, and only in Hubei pilot carbon prices are weakly linked to international natural gas prices (Fan and Todorova, 2017).

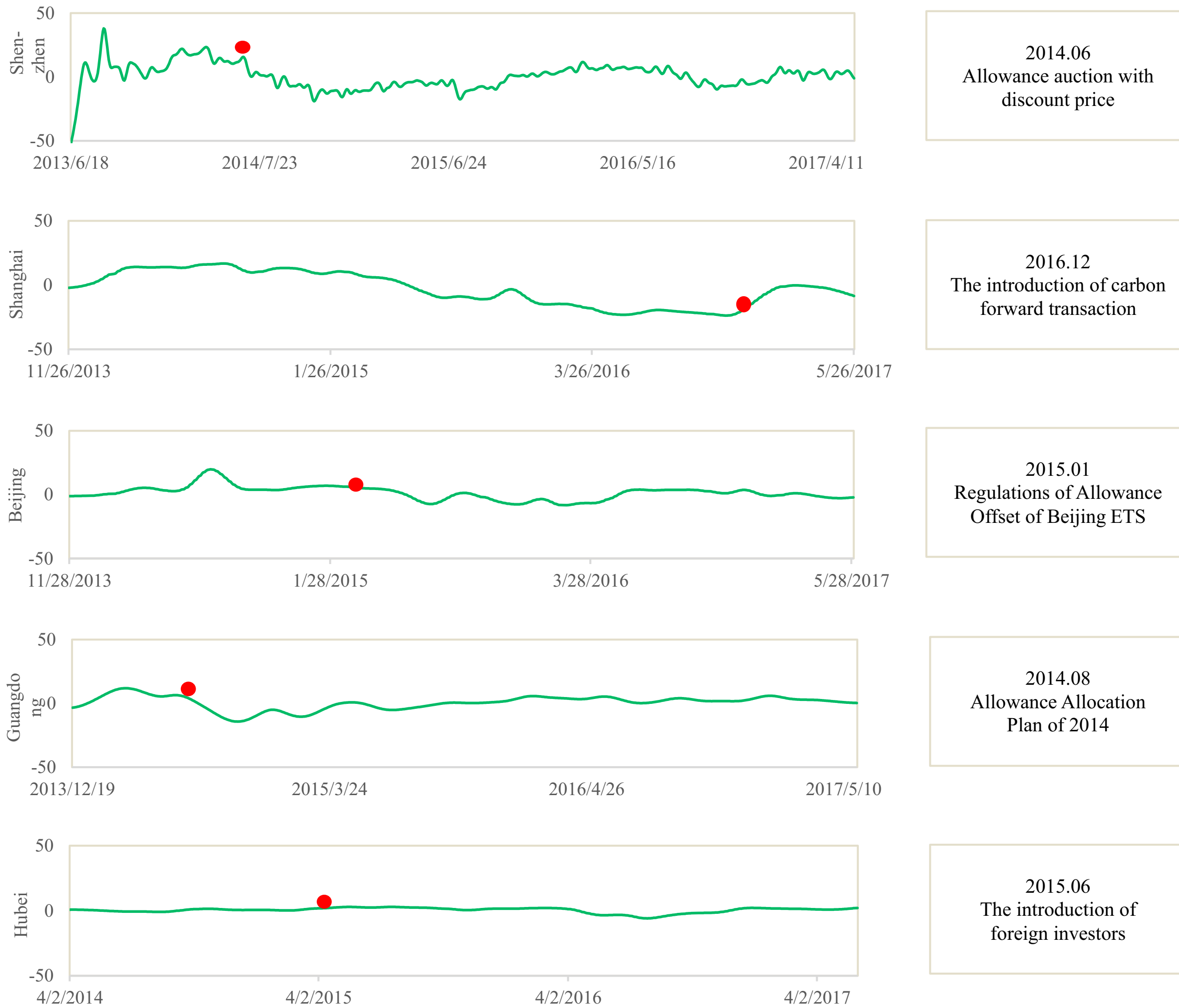

Fig. 4. Low frequency components of five pilots.
Note: The red dot means the starting point of the significant event listed on the right box. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

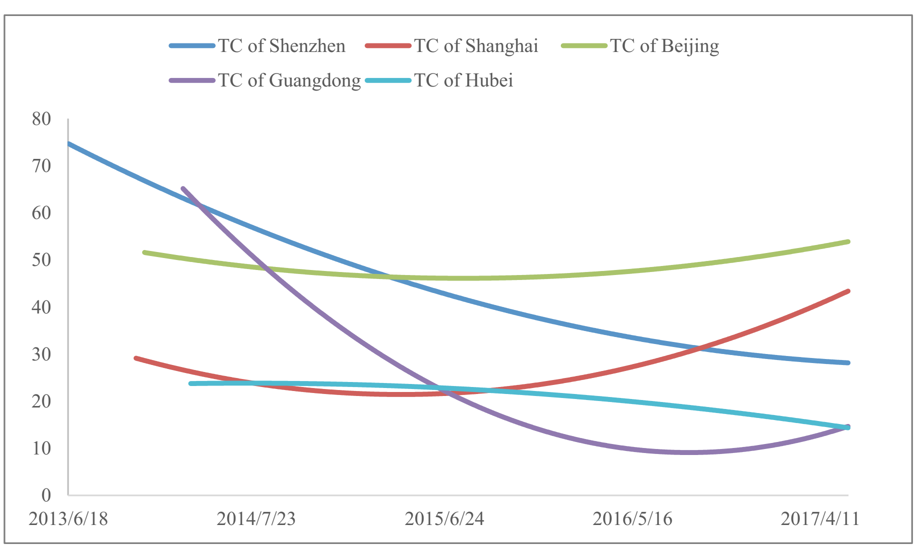

Fig. 5. Trend components of five pilots.

effects of short-term market fluctuations, significant events and the long-term trend. The main conclusions are as follows.

First, the average period and variance ratio of the IMFs vary over time. The IMF with a period around one year presents relatively higher variance ratios in five pilots, which reflects that pilots are characterized by the yearly cycle. In Guangdong pilot, the most influential low frequency IMF is the three-month factor which is related to its periodical auction regulation.

Second, short -term market fluctuations only exert limited influences on carbon prices, and the effects are usually within 15 RMB/ton of CO_2. The short-term fluctuations are violent in Shenzhen pilot, indicating that the pilot may exist serious speculative behavior. The impacts of short-term market fluctuations are decreasing in Shanghai and Guangdong pilots with increasing experience.

Third, significant events have greater impacts than short-term market fluctuations, and are the dominant driving force in Shanghai and Beijing pilots. The influences vary for five pilots, with up to 50 RMB/ton of CO_2 in Shenzhen, 15-25 RMB/ton of CO_2 in Shanghai, Beijing and Guangdong, and 7 RMB/ton of CO_2 in Hubei pilot. The regulation adjustments are the main source of significant events in the pilot markets.

Fourth, the long-term trend plays a decisive role in Shenzhen, Guangdong and Hubei pilots. The trend curves rely on the demand side factors such as macroeconomic growth, and the supply side factors including allocation plan and the stabilization mechanism. The price stabilization mechanism is critical to avoid a severe imbalance between demand and supply.

In light of the above findings, this paper suggests that the policy makers need to analyze the drivers of price fluctuations and take measures accordingly. For short-term market fluctuations, market plays a major role and government should only take precautions against over-speculation. For significant events, policy adjustments themselves are the major source, and may increase carbon price fluctuations. Therefore, government should consider the impact of policy adjustments, and avoid excessive influence on carbon prices. As to the long-term trend, the government should deliberately determine the cap and set up necessary stabilization mechanism to maintain relative scarcity of carbon allowance.

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