Price Bubbles in Beijing Carbon Market and Environmental Policy Announcement

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Abstract

This paper examines price bubbles in the relatively new carbon emission trading scheme of Beijing carbon market by employing a recently proposed econometric test which can stamp the occurrence and burst of financial bubbles. We find multiple bubbles in Beijing carbon market over the sample period between January 2014 to April 2018, and that the occurrences of carbon price bubbles are closely related to the announcements of environmental policies by the Chinese government. Comparing our results to the EU ETS, we find that the volatility of carbon price in Beijing market is higher than EU, and interestingly, the bubbles in Beijing market occur when the price volatility is relatively low, while in EU market the bubbles correspond to the peaks of volatility. Our empirical results provide insightful policy implications in the context of the actual China's carbon market reform. To achieve effective stabilization of carbon price, policymakers should publicize alert notifications of the price fluctuations, and strengthen the carbon markets supervision and promote its improvement.

Key words: carbon price, Chinese ETS, multiple bubble GSADF test

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1 Introduction

With increasing concerns for greenhouse gas emissions, regional and national efforts to cut down carbon dioxide has been emphasized and progressed over the past few years all over the world. Carbon emissions trading system, introduced as an efficient market-based instrument, has played an important role in the effective mitigation in many countries around the world. According to the World bank, international carbon market could reduce 30% abatement cost by 2030 and more than 50% reduction by the middle of the century[1].

China, the world's fastest-growing major economy, is on the way to slow down greenhouse gas emission. Before the Copenhagen Climate Change Conference 2009, Chinese government pledged to decrease per unit of gross domestic product CO2 by 40-45% below 2005 levels by 2020. In 2016, the Thirteenth Five-Year Plan issued by the National Development and Reform Commission (NDRC) declared China's goal to further cut down unit GDP CO2 emissions by 18% by the end of 2020 with 2015 as the base year. As one of the important measures to reach these goals, China has launched eight regional carbon market pilots[2] since 2013, which by design are similar to the European Emission Trading Scheme (EU ETS), the largest carbon market in the world. Although the eight regional markets cover a small share of total carbon emissions in China, the experiences and lessons of these pilots can present vital insights for the upcoming national emission trading scheme. At the end of 2017, China NDRC announced the national carbon emission trading scheme (ETS). If this program proves successful, it is expected to be the world's largest ETS surpassing the European counterpart EU ETS.

In the pilot regions, the total amount and intensity of carbon emissions decreased remarkably. By the end of October 2019, the trading volume of China's eight pilot markets has reached 347 million tons of carbon dioxide equivalent, which is about 7.68 billion yuan, and the overall compliance ratio of each pilot area has also exceeded 99%[3]. Nonetheless, the regional markets has shown some sort of weakness and the national ETS will confront with several challenges (Goulder *et al.*, 2017). One of them is that, while a stable carbon price is very beneficial to the operation of carbon market and the development of the economy in the long run, the carbon prices in the eight pilot carbon markets behaved in different manners in 2017-2018, as shown in Table 1. For instance, price in Chongqing exhibits the minimum mean and maximum stand deviation and left skewness, while Tianjin has the highest kurtosis.

Table 1. Summary statistics of carbon price in 2017-2018 (Yuan/ton)

[1] State and Trends of Carbon Pricing 2017, World Bank, *Ecofys*, Vivid Economics, Washington, DC.
[2] See Table 1 for the summary statistics of carbon price in the eight regional markets in 2017.
[3] http://www.chinanews.com/cj/2019/12-11/9031271.shtml

Market	Mean	S.d.	Skewness	Kurtosis
Beijing	50.864	1.47	0.723	0.439
Guandong	14.181	1.448	0.789	1.398
Shanghai	33.331	4.009	-0.344	-1.124
Shenzhen	33.818	2.092	0.776	0.879
Chongqing	6.49	6.958	1.33	-0.127
Hubei	15.348	1.85	0.048	-0.925
Tianjin	11.301	2.977	0.138	-2.195
Fujian	30.485	6.067	-0.03	-1.63
Overall sample	24.477	3.359	0.429	-0.411

Many literatures have explored the volatility of carbon price and its influential factors. In mature carbon emissions trading systems, the main factors affecting carbon price are broadly classified into the following categories. Firstly, the most widely accepted factor is the energy price, because energy sources are the main determinants of CO2 (Mansanet-Bataller *et al.*, 2007). Specifically, there is negative relation between crude oil price and carbon price, and an increase in natural gas or coal price generates a decrease in carbon price, and changes in electricity price may exert a positive effect on carbon price (Hammoudeh *et al.*, 2014a, b). Changes of crude oil, natural gas, coal and electricity may have the asymmetric and nonlinear impact on carbon price in US (Hammoudeh et al., 2015), but carbon prices co-move only weakly with energy prices, and their link to oil and gas prices is negative (Chevallier *et al.* 2019). The second factor is economic and financial activities. Although we cannot explain 90% of the price volatility in EU ETS, variations in economic activity are an obvious reason (Koch *et al.*, 2014). For instance, Financial options market provides a mechanism to hedge the uncertainty of future spot prices and reduce the volatility of carbon price (Xu *et al.* 2016). Stock returns also affects carbon market price, there is strong information interdependence between carbon price returns and European electricity companies' stock returns(Ji *et al.* 2019). Besides, carbon emissions trading market has a positive effect on the excess returns of companies participating in carbon emission allowances trading, the carbon premium in stock returns has increased after the establishment of carbon market (Wen *et al.* 2020). Thirdly, studies such as Ellerman and Buchner (2008) and Feng *et al.* (2011) provided evidence that market structure are the key factor of carbon prices volatility in EU ETS, while Jaehn and Letmathe (2010) documented that besides market structure, asymmetric information, interdependence between the carbon price and price of primary goods are also crucial factors. Lastly, a few papers consider extreme temperature as an basic factor. In the phase I of EU ETS, carbon price to some extent related to temperature (Hintermann, 2010), not only to extreme temperature, but also to unexpected temperature (Alberola *et al.*, 2008). In China's Shenzhen carbon market, the carbon price is more sensitive to coal, temperature and AQI (air quality index) than to other factors (Han *et al.* 2020).

However, carbon emissions trading market is also a financial market, there inevitably exists speculation which may induce the carbon price far exceed fundamental values. The speculation factors could give a satisfactory explanation for some drastic rise and crash in prices.

In fact, bubbles, as an economic phenomenon, generally arise from speculative investments. The main purpose of this kind of investment is not to make profit, but to obtain the price difference of asset price, which has obvious short-term behavior characteristics. With the development of carbon market, carbon emissions quota is considered as a profitable investment asset displaying speculative attribute. According to Hintermann (2008), there existed carbon price bubbles driven by a speculative factor. Cretf and Joets (2017) also demonstrated there are multiple bubbles in this market, which cannot be incurred by carbon price fundamentals. In China, carbon market is in early stage of development, carbon fundamentals are weak and markets are immature (Fan and Todorova 2017). Due to the asymmetric leverage effect and huge regional difference, China's carbon market provides strong arbitrage opportunities (Chang *et al.* 2017).

The contributions of this paper are threefold: First, to our best knowledge, no research has been found to detect price bubbles in China's carbon market so far. EU ETS has been tested for the presence of price bubbles, while no paper investigates bubbles in China. Second, unlike commonly used econometric detection techniques, we employ a testing method developed recently for detecting multiple bubbles. This approach was presented by Phillips and Yu (2011), Phillips *et al.* (2011), Phillips *et al.* (2015a and 2015b), and then was employed to examine multiple bubbles in iron ore price (Su *et al.* 2017a), crude oil price (Su *et al.* 2017b) and copper price (Su *et al.* 2020). Although Cretf and Joets (2017) have used this method to detect price bubbles in carbon market, it was first exploited to test bubbles in China. Last, we use detailed carbon market price information to address the relation between price bubbles and policy events. We found that China's carbon price is inconsistent with market fundamentals, and several price bubbles are detected over the period of 2014-2018 which could be explained by the possible policy events. Furthermore, price volatility and price bubbles did not occur at the same time, which indicates that speculative factors are less likely to work.

This paper is organized as follows. In section 2 we briefly introduce the bubble testing procedure. Section 3 presents the empirical testing results of multiple bubbles in Chinese ETS and their determinants with discussions. Section 4 concludes the paper.

2 Bubble testing procedure

Within the ETS framework, Carbon emission allowances are considered as tradable financial assets, see for instance, Oestreich and Tsiakas (2015). If the time series of prices of an asset exhibits explosive behavior, there is said be bubbles in the price. Traditionally, unit root and cointegration tests relying on a recursive right tailed ADF unit root test are used to detect explosive behavior. This category of test was criticized by Evans (1991) for lacking of power when faced with periodically collapsing bubble process. Phillips and Yu (2011), Phillips *et al.* (2011, 2015a and 2015b) proposed the supremum ADF (SADF) and the generalized SADF (GSADF) tests based on forward recursive regression technique. The advantages of the two tests over the traditional ADF based test of bubble are that, the SADF test has bigger power than the ADF test in the presence of periodic bubbles, and the GSADF test is a generalized version of the SADF test and it is able to detect multiple bubbles as well as to date stamp the origination and collapse of the bubbles. Our research goal can thus be well achieved by implementing the two tests on the time series of carbon price.

To detect a bubble or multiple bubbles, the first question is how to model the price of an asset and how it is linked to a potential explosive process. Phillips *et al.* (2015b) make the choice of picking a quite largely used model following the equation

$$P_t = \sum_{i=0}^{\infty}(\frac{1}{1+r_f})^i \mathbb{E}_t(D_{t+i} + U_{t+i}) + B_t, \tag{1}$$

where P_t is the after-dividend price, D_t is the dividend (payoff of the asset), r_f is the risk-free interest rate, U_t is the unobservable fundamentals, B_t is the bubble component. Then, $P_t^f = P_t - B_t$ is the market fundamental. Moreover, B_t satisfies the submartingale property: $\mathbb{E}_t(B_{t+1}) = (1 + r_f)B_t$ which means that in case of bubble the process of P_t will be explosive.

The intuition behind the SADF and GSADF method is: if there is no bubble ($B_t = 0$), the degree of nonstationarity of the asset price, P_t, is controlled by the market fundamental constituted of dividend and unobservable fundamentals series. Therefore, when unobservable fundamentals are at most $I(1)$ and D_t is stationary after differencing, empirical evidence of explosive behavior in asset prices may be used to conclude the existence of bubbles.

Phillips *et al.* (2015b) suggests to use a recursive approach with a rolling window ADF style regression to test bubble. Suppose the rolling window regression sample starts from the r_1^{th} fraction of the total sample T and ends at the r_2^{th} fraction of the sample, where $r_2 = r_1 + r_w$ and r_w is the (fractional) window size of the regression, then, the empirical regression model can then be written as:

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \psi_{r_1,r_2}^i P_{t-i} + \epsilon_t, \tag{2}$$

where k is the lag order, $\epsilon_t \overset{iid}{\sim} (0, \sigma^2_{r_1,r_2})$ and y_t is the price of an asset. The test for the bubble is a right-tail variation of the standard ADF unit root test. The null hypothesis is of a unit root ($H_0 : \beta_{r_1,r_2} y_{t-1} = 1$) and the alternative is of an explosive autoregressive coefficient ($H_1 : \beta_{r_1,r_2} y_{t-1} > 1$).

Let $ADF_{r_1}^{r_2}$ denotes the ADF statistics (t-ratio) based on this regression. The $SADF$ test operates on repeated estimation of the ADF model on a forward expanding sample sequence. The test is obtained as the supremum value of the corresponding ADF statistic sequence. The window size r_w expands from r_0 to 1; so that r_0 is the minimum window width fraction (initialising computation) and 1 is the largest window fraction (the total sample size) in the recursion. The starting point r_1 of the sample sequence is fixed at 0; so the end point of each sample (r_2) equals r_w, and changes from r_0 to 1. The ADF statistic for a sample that runs from 0 to r_2 is denoted by $ADF_0^{r_2}$. Therefore, the SADF statistic is defined as

$$SADF(r_0) = \underset{r_2 \in [r_0,1]}{sup} ADF_0^{r_2}. \tag{3}$$

The difference between the SADF and GSADF is that besides varying the end point of the regression r_2 from r_0 (the minimum window width) to 1, the GSADF test allows the starting point r_1 to change within a feasible range, i.e. from 0 to $r_2 - r_0$. As explained in the last section, this is what makes GSADF more accurate on longer datasets as the subsamples used in the recursion are much more extensive than those of the SADF test. They denote $GSADF(r_0)$ the GSADF statistic over all the feasible ranges of r_1 and r_2:

$$GSADF(r_0) = \underset{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}}{sup} \{ADF_{r_1}^{r_2}\}. \tag{4}$$

In the case of a rejection of the null hypothesis, SADF and GSADF methods enable us to estimate the start and end points of the bubble (or bubbles). Table 2 shows the difference between ADF, SADF and GSADF test: the three tests share the same null hypothesis (H_0: Unit root) but SADF test for a single bubble whilst GSADF test for multiple.

Table 2. Comparing ADF, SADF and GSADF

Test	Null hypothesis	Alternative hypothesis
ADF	Unit root	Explosive process
SADF	Unit root	Single periodically collapsing bubble period
GSADF	Unit root	Multiple periodically collapsing bubbles

3 Empirical results

3.1 Data

Specific information on all variables are shown in Table 3. Considering the carbon emission trading market liquidity and the price stability,this paper chooses carbon emissions trading data one year later as the research sample. China's carbon emissions trading market started in 2013, and the last pilot market, Fujian carbon market, was established in December 2016. From then on, all eight pilot carbon markets in China have been established. Therefore, we use daily time-series carbon price data from January 1, 2014 to April 2018 in the bubble analysis. The fundamental variables of economic activity and energy price are selected monthly over the same period.

Table 3. variables and data sources

Category	Variable	Content	Sources
Carbon price	bea	Beijing carbon emission trading closing price	Beijing environment exchange
Economic activity	mpi	China's macroecomic prosperity index(consistent index)	China's National Bureau of Statistics
Energy price	coal	Medium steam coal price index in China	Wind Data
	gas	Natural gas price in north China	Wind Data
	oil	Daqing crude oil price	Wind Data

Beijing carbon emission trading scheme began at November 28, 2013 and has been in operation for more than four years. By the end of December 31, 2017, Beijing carbon market had traded a total of 20.13 million tons of carbon allowances and had turned over more than 700 millions RMB, accounting for 11.03 percent and 19.44 percent of national level separately. Since its opening, Beijing carbon market has developed smoothly and safely, the volume of transactions expanded gradually. According to Beijing environment exchange, the closing price in Beijing carbon market is the most stable in China, average transaction price is about 50 yuan/ton, the highest daily price is 77 yuan/ton, the lowest is 32.4 yuan/ton in the four-year period. We edit out all daily data with zero trading volume and obtain the carbon price data for research.

The macroeconomic activity of a country may affect the carbon market price. During a booming period, enterprises will expand its production scale and demand for carbon allowances will increase correspondingly, which will lead to a rise in the carbon price. Economic activity is often proxied by stock market index, for instance, Dow Jones Euro Stoxx 50 (Cretí and Joëts, 2017b) and China's Shanghai Shenzhen 300 index (Zeng et al., 2017). However, China's stock market is neither semi-strong nor weak form efficient(Ma, 2017). Given the inefficiency of China's stock market, it does not fully reflect the China's economic situation. Therefore, we choose China's macroeconomic prosperity index as the economic activity variable and use its consistent index to stand for the basic trend of current economy.

As the main cause of carbon dioxide emission, fossil energy, represented by coal, oil and gas, still accounts for a large proportion of China's energy consumption. Thus, we select above three energy prices as the primary drivers in this paper. China's medium steam coal price index is used as substitute price for coal variable , gas variable is average natural gas price in north China, and oil variable is Daqing crude oil price. All the data are from WIND database.

3.2 Carbon price fundamentals

Since there is no dividend in carbon price in contrast to stock price, based on equation (1) , carbon price can be written in terms of two components: the traditional fundamentals and uncertainty price bubbles:

$$P_t = F_t + B_t, \tag{5}$$

where F_t denotes the fundamentals of carbon price which corresponds to the first term in equation (1) .

In a initial stage of carbon emission trading system , a set of widely accepted price fundamental drivers included are energy prices and economic activity. Evidently, energy prices are the most common driver of carbon price, we thus consider the oil price, coal price and gas price in China. Economic activity is indicated by China's macroeconomic prosperity index.Economic activity and energy prices are the fundamentals of Beijing carbon market price. We put together mpi, coal index, gas and oil price, then after running data standardization, we statistically estimate the fundamental component in terms of the first principal component of the four drivers:

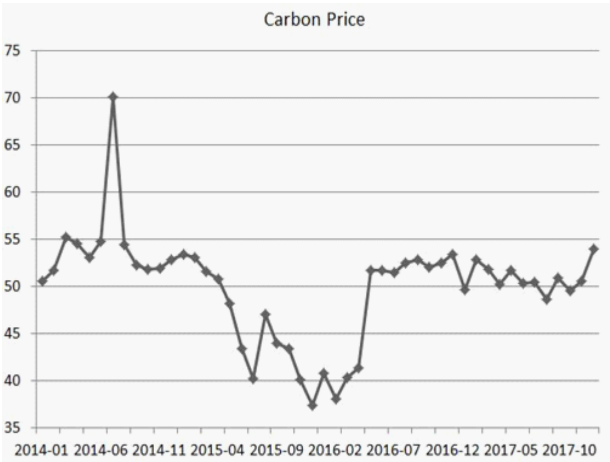
$$F_t = 0.411mpi + 0.393oil - 0.150gs + 0.273coal \tag{6}$$

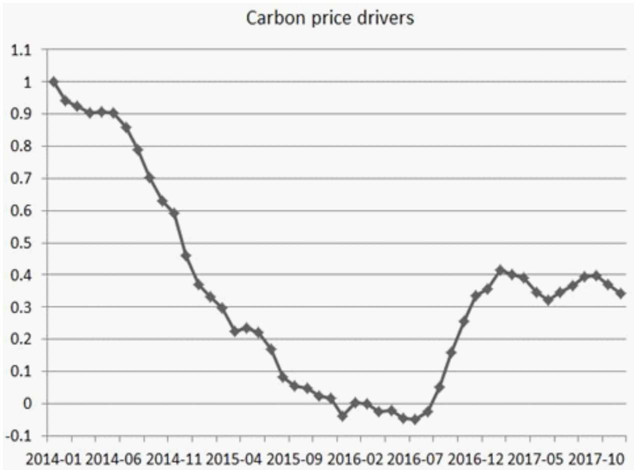
The equation (6) can explain about 59.5% of the four considered drivers. Based on the equation, the behaviors of carbon price fundamental is reported in Fig.1, the dynamics of carbon price is also depicted in Figure.1.

Given the divergence in trends of carbon price and fundamentals, we argue that the determinants of carbon price are policy events characterizing environmental regulation and energy rules. We hand-collect sample events in 2014-2018 from China national development and reform commission , Beijing municipal commission of development and reform and Beijing municipal environmental protection bureau . The search keywords included carbon emission trading, carbon price, energy and environmental pollution. Only the major regulatory polices and rules are covered. Systematizing those events, we find that carbon price bubbles always occur in the days before or aftermath of some events.

The events methodology is similar to the one applied by Koch *et al.* (2016) and Cretí and Joëts (2017a).

Figure 1. Carbon price and its main drivers (2014-2017)





As we can see from Figure.1, the trends of carbon price and its fundamentals are totally different, carbon price fundamentals can not illuminate the change of carbon price in 2014-2017. Carbon price drivers declined sharply from nearly 1 in January 2014 to negative in January 2016, and climb up slowly in the next few months, while carbon price remained almost unchanged, except two structural breaks, the first one is in July 2017, when the first commitment period come up in carbon market, the second one is in the period when all seven pilot carbon market operated successfully. There are very few individual and institutional investors in China carbon market, most of the participants are enterprises that have the compulsory carbon reductions obligations, those enterprises are more rational than individuals, therefore, carbon price is also less sensitive to the speculative factors.

3.3 Periodical collapsing bubbles

In this section we report the tests results for periodical collapsing bubble for the overall sample period with a minimum window of 35 days. In table 4 both SADF and GSADF indicate significantly the presence of bubbles in the sample.[4]

Table 4. Test statistics for periodically collapsing bubble

Test statistic		Finite sample critical values		
		90%	95%	99%
SADF	2.59***	1.284	1.541	2.099
GSADF	7.048***	2.204	2.418	2.949

Table 5 shows that we detects fourteen bubbles over the sample period. During 2014, there are one mild explosive bubble and three longer episodes lasting more than five days. Four bubbles occur in 2015, whose duration ranges from one to more than five days. 2016 is characterized by one short bubble and two of five days ones, whereas one short and one longer bubble in 2017, and one long bubble in early 2018. Overall, there are ten big bubbles, one of three days bubble and nine of one day bubbles. The fact that there are more big bubbles than one day small bubbles suggests that Beijing carbon market is still immature.

Table 5. Number of bubbles[5] in carbon price (Jan 2014- April 2018)

Year	h=1	h=3	h=5	h>5
2014	1	0	0	3
2015	1	1	0	2
2016	1	0	0	2
2017	1	0	0	1
2018	0	0	0	1

Table 6 reports the explosive periods over the sample period, where the test statistics are above the critical values as shown in table 4. Both the originating and bursting dates are stamped by the tests.

Table 6. Occurrence of price bubbles (Jan 2014- April 2018)

[4]Notes: Critical values from both tests are obtained by wild bootstrap approach from Monte Carlo simulation with 1000 replications. The smallest window has 35 observations. ***, ** and * denotes a rejec-tion of the nul hypothesis at 99%, 95% and 90% signi cance levelsrespectively.

[5]In the table, h is the minimum amount of days for a bubble to be considered.

Year	h=1	h=3	h>5
2014	25th July		10th Mar-28th Mar 28th Apr-8th May 26th Jun-21st July
2015	7th Jan 27th Jan 24th Dec	6th Mar - 9th Mar	17th Mar-10th Apr 14th May-19th Aug
2016	27th Jun		11th May-17th May 22nd Nov-28th Nov
2017	11th May		26th Apr-8th May
2018			7th Feb-22nd Mar

To see the occurrence of bubbles in more details, figure 2 shows the plot of backwards SADF sequence (in blue) and the 95% bootstrapped critical value sequence (in red). When the blue line goes above the red line, a bubble is identified. Moreover, we can carefully compare and discuss the movement of carbon price, the bubbles and volatility using figure 2-4. There are two interesting findings that are worth to note. First, three negative bubbles are found which are marked in red in table 6. A negative bubble happens when the price drops in an explosive way. For instance, the biggest negative bubble found in the sample is between 14th of May 2015 and 19th August 2015, see figure 2, while in this period the price was declining as shown in figure 3. Second, volatility plotted in figure 4 does not seem to increase when bubbles are found. While comparing the carbon market of Beijing and the EU, it can be seen that the volatility of the former is much higher.

Figure 2. Backwards SADF sequence

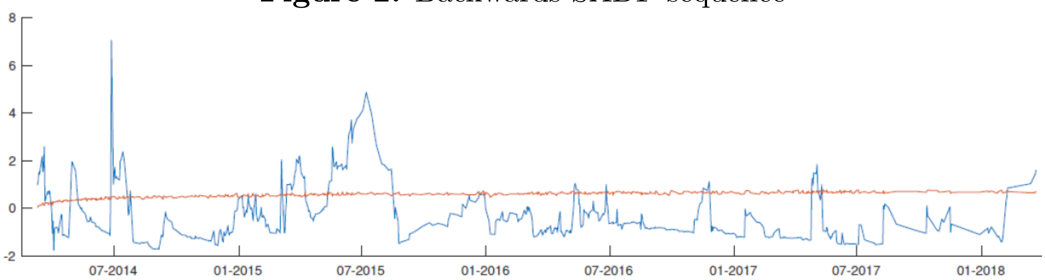


Figure 3. Chinese carbon price

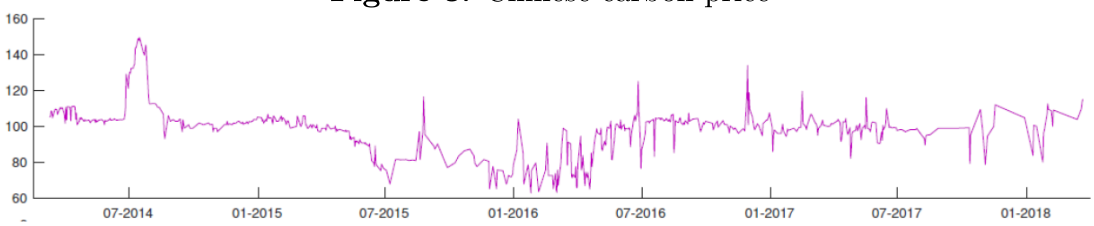
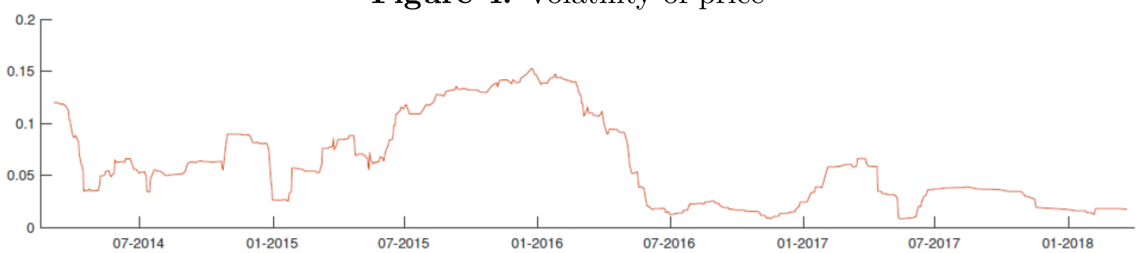


Figure 4. Volatility of price



3.4 Environmental policy announcement and bubbles

To explore what is behind the occurrence of bubbles of carbon price, we list the events and corresponding explosive bubble periods in table 7. These events contain carbon market, climate change, environmental pollution and energy saving regulations. It exhibits a consistency between the announcement of these policies and the occurrence of bubbles.

Table 7. Regulatory events concomitant to the bubbles

year	period	events
2014	January-March	Air pollution prevention regulations 22nd Jan
	April-May	Environmental protection law 24th Apr
		Action plan for energy saving and emission reduction 26th May
	June-July	First compliance period 5th Jun
2015	January	Carbon emissions trading interim regulations 1st Jan
	March-April	Submission of carbon emissions verification report 23th Mar
		Environment bulletin 16th Apr
	May-August	Compliance period 5th Jun
		Hearing for national carbon emission trading regulations 29th July
		Air pollution prevention and control law 29th Aug
	December	Notification of carbon emissions trading pilots 25th Dec
2016	May-June	Industrial energy saving regulations 13th May
		Compliance period 5th Jun
	November	Pollutant emission permit implementation plan 10th Nov
		Ecological environment protection plan 24th Nov
2017	April-May	Implementation scheme of discharge standard in industrial pollution source 10th May
		Compliance period 5th Jun

To see this consistency in further detail, we conduct event analysis on the specific dates of each of the 14 bubbles. First and foremost, big bubbles always come up near the commitment period which is 5th June in Beijing. These explosive periods, such as 26th Jun-21nd July 2014, 14th May-19th Aug 2015, 11th May-17th May 2016 and 26th Apr-8th May 2017, last more than five days. A sensible explanation is, in order to complete their annual reduction compliance, many traders start their businesses in carbon market, buying or selling quota allocations, trigger the trade behavior change and push up carbon price in short time, as we can seen from Figure.1. Huge volumes and high prices occur in almost one month, which generates price bubbles. Secondly, bubbles (10th Mar-28th Mar, 28th Apr-8th May, 25th July) occur in the initial stage of Beijing carbon market, as table 6 documents one mild bubble and three big bubbles in the first half year of 2014. Carbon market is a newborn thing in China, most regulated firms are wondering whether local governments take real actions to punish those who do not fulfill reduction targets. Very few participants in carbon market trade with high price deviating from the real value most other traders deemed. In the third, commissioners' announcements, which are concomitant to the bubbles on 7th Jan, 27th Jan, 6th Mar-9th Mar, 17th Mar-10th Apr, 24th Dec in 2015, 22nd Nov-28th Nov in 2016, stress the enforcement of environmental regulations and impact the traders' expectation of deregulation, which leads to the greater demand of quotas. Lastly, as depicted in Table 6, there is no bubbles at the end of 2017. Participants in Beijing carbon market become more and more rational, carbon price also gets stable.

3.5 Comparison to EU ETS

Since the EU ETS is a much more mature market than the Chinese ETS, it is worth to compare the two in terms of bubbles. To do this, we repeat the tests that are conducted for the Chinese market on EU ETS over exactly the same period[6]. Tests results are reported in table 8, and number of bubbles in each year in the sample are reported in table 9. Plot of SADF test statistic can be found in figure 6 which can help stamp the dates of bubbles.

The value of both the SADF and GSADF tests reject the null hypothesis of no bubbles for the EU ETS. However, while comparing with the result of the Beijing Market, the test reject less strongly. The EU market is most likely less explosive. This conclusion is supported by the comparison between figure 5 and figure 3 illustrating the carbon price curve. The values of the Beijing curve shows much more variations. Even though, the GSADF test's value is lower and the price curve is more constant, the test and many more short-lived explosive episodes. However, most of those episodes are shorter than the ones found in the Beijing market.

While comparing the volatility of carbon markets of Beijing and the EU, it can be seen that the volatility of the former (shown in figure 4) is higher than the EU (shown in figure 7) in most of the time. Indeed, it peaks in 2016 at a level of 0.16 in Beijing market, where 0.058 is the highest value reached by EU's carbon market.

Table 8. Test statistics for bubbles in EU ETS

Test statistic		Finite sample critical values		
		90%	95%	99%
SADF	1.033*	1.012	1.467	1.933
GSADF	3.714***	1.836	2.079	2.458

Table 9. Number of bubbles in carbon price in EU ETS (Jan 2014- April 2018)

Year	$h = 1$	$h = 3$	$h = 5$	$h > 5$
2014	2	0	2	3
2015	2	3	0	1
2016	3	1	1	5
2017	4	0	0	5
2018	0	0	0	1

Figure 5. EU carbon price

[6] EU ETS data are obtained from Datastream.

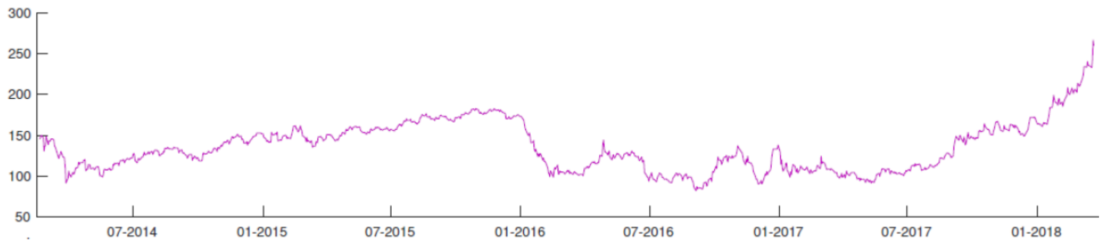


Figure 6. Backwards SADF sequence

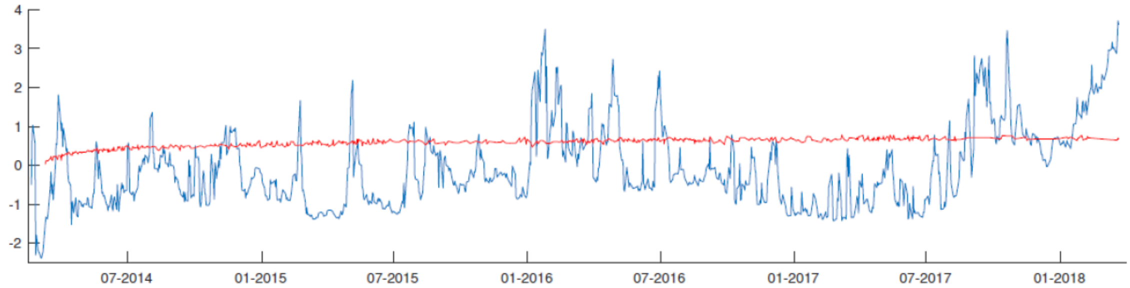


Figure 7. Volatility of price of EU ETS[7]

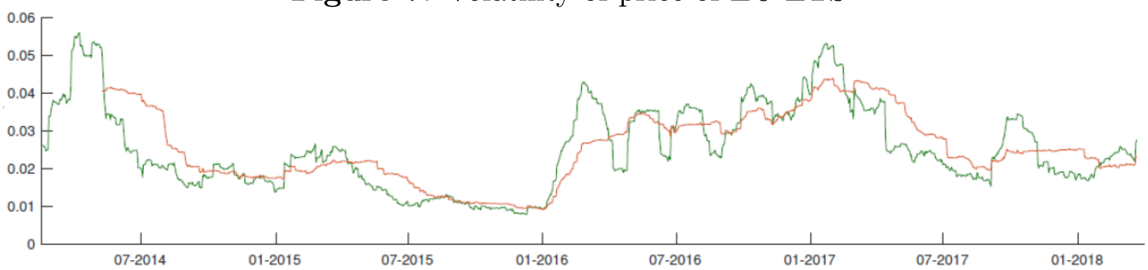


Figure 8. Trade volume of Beijing Market

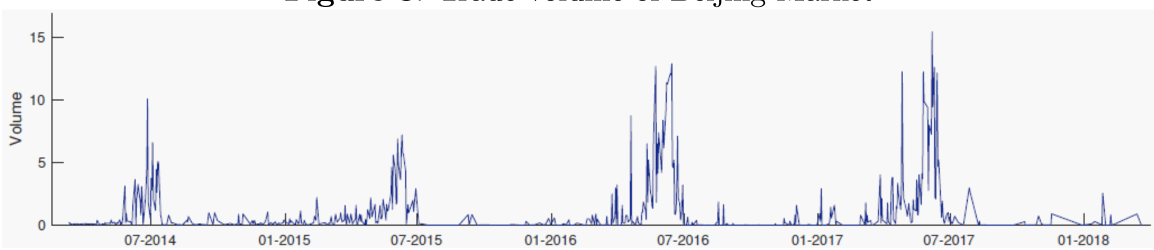
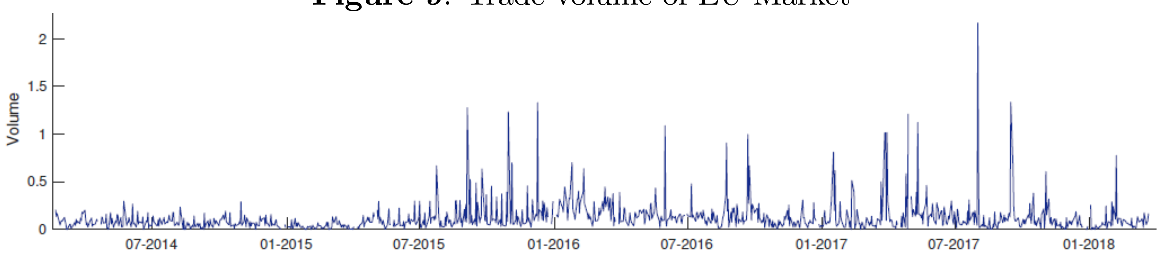


Figure 9. Trade volume of EU Market



While comparing figure 8 and figure 9, it is clear that the volumes are much higher on the EU market. Interestingly, in Beijing market most explosive periods show also an increase in volume. However, the comovements in the EU market of bubble and trade volume are not as clear as in the case of the Beijing market.

[7]Here the volatility is calculated by two ways since there are some difference between the two. The first one is the volatility compared to the last month (green) and the other one compared to the last three months (red).

Like explained in the previous section, it appears that the EU market experience much lower volatility level than the Beijing market. A very interesting difference is, the peaks of volatility of EU carbon price correspond to the bubbles, and this co-movement was not found in the case of the Beijing market. On the contrary, bubbles in Beijing market seems to happen when the price volatility are relatively low, for instance, see the bubbles in July 2014, between March and April 2015, and between April and May 2017. While the volatility was at the highest level around January 2016, there was no bubble found in Beijing market.

3.6 Robustness check

In our tests we use the size of minimum window as 46[8]. To check if our results are sensitive to minimum window size, we perform both the SADF and GSADF tests using different minimum windows: 35, 55 and 65. As shown in table 10, in all three cases the null hypothesis of no bubble is rejected, which means our results are robust to the choice of minimum window size.

Table 10. Effect of the size of minium window

Test statistic	size of minimum windows		
	35	55	65
SADF	1.735**	2.419**	2.765*
GSADF	4.871***	3.960***	3.286**

4 Conclusions

In order to investigate the efficiency of Beijing carbon market, in this paper we test and have found multiple bubbles in Beijing carbon market over the period of January 2014 and April 2018. One of our major findings is that, most of those bubbles occurred when there were environmental polices announced by the government. A possible explanation of this result is, the vast majority participants (traders) in the market are state-owned firms, therefore these firms are very likely to be affected by environmental policies issued by the government. This suggests that to make the carbon market as an efficient tool to reduce carbon emission, the Chinese government can encourage more private firms to have access to this market.

Since the Chinese carbon trading scheme is relative new, we also compared our results from Beijing market to the more mature EU ETS. We have found some interesting differences between the two markets. First, it appears that explosive moments (bubbles) in the Beijing carbon market present a similar pattern to the trading volume. This is not the case for the EU carbon market. Even though most explosive periods in EU market

[8] This is decided by choosing $r_0, r_1, ...$ in equation (3) and (4), See more details in Phillips *et al* (2015).

show also an increase in volume, the comovements are not as clear as in the case of the Beijing market. Second, the Beijing carbon market volatility is really high but does not appears to change significantly at explosive periods. In fact, our empirical evidences show that the EU carbon market exhibits a clear pattern of increased volatility during or just before bubbles. while in Beijing market not all the changes in the level of volatility are linked to a bubble.

Our analysis presents some policy implications for the development of Chinese carbon emissions trading markets. First, policymakers should not only pay attention to the spot price impact factors, but also forestall and defuse speculative factors in the initial stage of carbon markets. In December 2017, China national carbon trading market was formally established. With the rapid development of the carbon market, relevant policies and regulations are being perfected. Policymakers should formulate and improve relevant policies and regulations as soon as possible, guide market participants to invest rationally and curb the aggregation and spread of price bubbles. Second, policymakers should also publicize alert notifications of the price fluctuations. Given the current system is not perfect, there is a serious risk asymmetry, when the market is obviously abnormal, policymakers should timely release risk hints, guide market participants to make rational decisions, and prevent the possible causes of the bubbles. Finally, policymakers should strengthen the supervision and promote the improvement of carbon emissions trading markets. Information economics theories point out that information asymmetry and market imperfection will make the market be in an unbalanced state for a long time, and it is difficult to correct the deviation of equilibrium price by relying on the market itself. Therefore, it is very important to establish a scientific and timely price supervision mechanism and minimize the impact of information asymmetry on market participants.

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