3rd International Conference on Public Policy (ICPP3)
June 28-30, 2017 – Singapore

Panel T01P04 Session 1
Mechanisms of Local Policy Experimentation in China

Title of the paper
Policy Design and Implementation of ETS Pilots in China

Author(s)
Lili, Li, LKYSPP, National University of Singapore, Singapore, li.lili89@u.nus.edu

Date of presentation
June 30th 2017

Policy Design and Implementation of ETS pilots in China

Lili Li
Lee Kuan Yew School of Public Policy, National University of Singapore, Singapore;
li.lili89@u.nus.edu

Abstract: This study investigates the design and implementation of emission trading scheme (ETS) for reducing energy-related emissions in China, focusing on the market efficiency and carbon price drivers. This study first compares the policy design of China ETS in relative to EU ETS. Second, it tests the weak-form efficient market hypothesis and found that all ETS markets were informationally inefficient. Third, it analyzes the short-and long-run causal effects between carbon prices and energy prices. Results show that carbon prices between ETS pilots are co-integrated, but this is not true for every two ETS pilots. Also, energy prices have both short and long-run dynamic effects on carbon prices. At the end, this study examines the structural breaks of carbon prices.

Keywords: Emission trading, design and implementation, market efficiency, carbon price, energy price

1 Introduction

The strong interest in using "New Environmental Policy Instruments" (NEPIs)--including economic instruments that emphasize market incentives and suasive instruments that encourage voluntary environmental changes, in contrast to traditional direct government command and control (GCAC) approaches, has been prevalent in developed countries since 1980s, with numerous academic studies on their implementation and effectiveness. However, there is a lack of evidence illustrating the complexity in the design and implementation in relation to the effectiveness of the NEPIs in developing countries where environmental investments and regulatory capacity are low.

Economic instruments can be in the form of tradable permits, taxes, subsidies, charges, risk liability and so on (Bertoldi and Rezessy 2009; Wurzel, Zito, and Jordan 2013). The rationale behind economic instruments is the polluter pays principle that requires polluters to pay for the pollution that they cause. Greenhouse gas (GHG)[1] emissions have been attributed for the global climate change and emission trading scheme (ETS) is one of three mechanisms[2] for reducing GHG emissions that the Kyoto Protocol suggested. Carbon dioxide (CO_2) is the principal GHG, so hereafter CO_2 emission is not deliberately differentiated from GHG emission. ETS creates a market for CO_2 emission allowances so as to encourage the internalization of emission abatement costs. If the market functions well, carbon price (i.e. the price of CO_2 emission allowance) can reflect the marginal cost of emission reductions and encourage enterprises to adopt low-carbon measures internally. One of the major implementation concerns is that targeting participants fail to respond in ways anticipated by policy makers due to low economic incentives (Weaver 2010).

So far, ETS has been used for emission abatement in European Union (EU), United States (US), South Korea, Switzerland, New Zealand, Australia, Canada, Japan, Kazakhstan and China. China is the by far the second largest emitter of CO2 emissions, mainly caused by its huge size of population and economy and the high share of coal (more than 60%) in its energy mix (Olivier et al. 2015). Since 2013, China has developed seven domestic pilots of ETS, covering 5 cities and 2 provinces. Shenzhen ETS is the first ETS in China, which was established in June 2013. Now China is on its way to establish a nationwide carbon trading market, which will come into operation in 2017. Experiences from the pilots become references for the national ETS to be established.

This study aims at evaluating the implementation of ETS in China, by addressing features of

[1] GHG includes carbon dioxide, methane, nitrous oxide, hydroflurocarbons, perfluorocarbons and sulphur hexafluoride.
[2] The three mechanisms of reducing GHG emissions that the Kyoto Protocol suggested are Clean Development Mechanism (CDM), joint implementation, and emission trading.

the economic incentives provided by the policy instrument through carbon price development. Specifically, this study examines the price volatility, the weak-form efficient market hypothesis and the co-integrations between carbon markets. Then it explores drivers of carbon prices, focusing on structural breaks and the influence from energy markets.

2 Literature review

2.1 Theories surrounding ETS

The discussions surrounding economic policy instruments assume that the selection of policy instruments relates to the effectiveness in achieving environmental goals. Theory of policy design implies that policy effectiveness could be improved by better matching problems and a solution with a good consideration of possible policy instruments (de Leon 1992). And the main idea is for policy analysts to identify a group of policy tools that are routinely used, regardless of the policy domain (Howlett and Lejano 2016). Recent studies on policy implementation also address the relation between the selection of policy tools and the implementation success. However, there is no simple causal relation between the selection of policy instruments and implementation effectiveness (Knill and Liefferink 2007). In the environmental domain, given the complexities of environmental issues, economic instruments may not generate good performance in cases with limited monitoring and enforcement resources. Regarding ETS, the price development trajectory of EU-ETS may not be repeated in the carbon markets of China.

ETS is known as a “cap-and-trade” approach to control pollution. The “cap” sets levels of allowed emissions or assigned amounts. These emission allowance units can be considered as the right to emit pollutants. The “trade” creates a market and allow polluters to trade the allowance units. So, the emission allowance would be a new commodity in the market.

ETS has advantages over other pollution control tools. Most importantly, it is believed that ETS is the least-cost tool for emission abatement (Grubb et al. 2011). In an ETS, an entity can choose to reduce its internal emissions, sell excess emission allowances or buy allowances from other entities who face lower emission reduction costs. In principle, entities choose the most affordable compliance strategies, and each entity reduces its emissions only to the level when the marginal cost of reducing emissions internally equates to the cost of buying the same amount of allowances. Therefore, ETS theoretically works as an efficient environmental policy with low social cost.

However, ETS is criticized for its uncertainty. In practice, carbon prices are often low and with high volatility. For instance, the carbon price of EU-ETS once decreased to almost zero in its first carbon trading period from 2005 to 2007 (Alberola, Chevallier, and Chèze 2008). In those cases, industrial participants have little incentives to reduce internal emissions and have to adapt to the volatile market costly.

2.2 Empirical studies on carbon price development

There are many studies evaluating the implementation of ETS through carbon price analysis. Market efficiency, price volatility, and relationships between carbon prices and energy prices are the topics that are frequently brought up in this literature. Time series analysis techniques often for those studies are random walk model, co-integration test, Granger causality test, AR model, GARCH model, ARIMA model, VAR model, VECM model and so on (Chevallier 2012). As EU-ETS is the first and largest ETS scheme in the world[3], existing literature concentrates on the development of EU-ETS.

A main driver of carbon price identified in literature is energy price. Regression analysis, Granger causality test and co-integration analysis are the methods frequently used for the topic. Energy prices can affect carbon prices through their influence on energy demand (Chevallier 2012). Hintermann (2010) found that natural gas and coal prices affected the spot price of EUA (EU emission allowance) in 2006-2007. Alberola et al. (2008) found that the EUA price was

[3] EU-ETS covers more than 10 thousand entities across 27 member states (Chevallier, 2012).

related to the prices of Brent oil, natural gas, coal, electricity, and energy spreads. This group of studies focuses on the relationship between an ETS market and energy markets, but few studies test the relationship between two ETS markets, even though it is theoretically possible that carbon prices in one ETS market are affected by price signals from other ETS markets.

Literature also found structural breaks of price series driven by institutional decisions. For instance, Alberola et al. (2008) examined impacts of institutional decisions on European carbon prices from 2005 to 2007, and found that carbon price change had structural breaks following the disclosure of verified emissions or following stricter allowance allocation.

Price volatility is important for investment risk management purpose and price returns are often used for volatility analysis. Price returns can be calculated based on daily data or intraday data (Chevallier 2012). Let $Price_t$ be the logarithmic spot price at time t and the logarithmic price returns can be measured by $lnReturn_t = ln(Price_t/Price_{t-1})$ (Montagnoli and de Vries 2010). Byun and Cho (2013) used the absolute values of daily $lnReturn_t$ of carbon futures to create the volatility time series, and calculated the so-called "realized volatility" by averaging squared daily $lnReturn_t$ against sampling frequency m and then computing a square root (that is, calculating a standard deviation to show the daily variance of log returns). They found that Brent oil, coal, and electricity prices could efficiently forecast the daily volatility of carbon futures. Reboredo (2014), on the other hand, tested on the volatility spillovers between the oil market and EU-ETS market during Phase II (2008-2012) using a conditional AR model based on weekly carbon prices and crude oil prices.

Price returns data are not only used for volatility analysis, but also for testing the market efficiency of ETS. The weak-form efficient market hypothesis (EMH) is that a market is efficient if its current price effectively reflects all available information. Montagnoli and Vries (2010) examined the EMH for the EU-ETS using a random walk model to test randomness of spot price returns. If price returns followed a random walk, the market was considered as efficient. They concluded that the EU-ETS market was not efficient in Phase I (2005-2007), but it became efficient in Phase II. Later on, Daskalakis (2013) examined the EMH based on the price return data of carbon futures and also found that the EU carbon trading market achieved a weak efficiency from 2010 onwards, which implied that the EU ETS market was moving towards maturity.

2.3 Research question and hypotheses

In this study, the objective is to assess the implementation of the ETS policy instrument in China, with a focus on the carbon price development. The research questions to be addressed would be:

(1) Is ETS in China efficiently functioning and providing adequate economic incentives through carbon price development?

(2) How does a local ETS market relate to energy market or other local ETS markets in China?

Several hypotheses are brought up based on the aforementioned literature.

Hypothesis 1 The local ETS markets in China are informationally efficient as in the price return series follow a random walk.

Hypothesis 2 Carbon prices between two local ETS pilots in China are co-integrated.

Hypothesis 3 Carbon prices of a local ETS pilot in China are co-integrated with energy prices.

3 Policy design of local ETS in China

China respond to climate change by setting ambitious emission reduction goals. In June 2015, China submitted the report '*Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions* to the Secretariat of the United Nations Framework Convention on Climate Change (UNFCCC) and determined to decrease CO_2 emission intensity by 60–65% by 2030 compared with the 2005 level (NDRC, 2015). A set of policies and policy instruments has been undertaken to facilitate achieving the targets, including ETS. Traditional

GCAC approaches are found to be unable to achieve long-term energy efficiency and GHG reduction targets (Wang and Chen 2015). In particular, during the 12th FYP period (2010-2015), President Xi emphasized the necessity to use economic instruments in solving environmental issues, which was also given attention in the newly released 13th FYP. Lessons from the ETS pilots are not only necessary for building the national ETS scheme, but also inspiring for introducing other policy instruments of the same type to China.

In general, developing an ETS involves cap setting, allocation mechanisms of initial emission permits, monitoring and implementation, political issues, pollution permits, market definition, market operation, and the integration of the existing law and institutions (Stavins 1995; Zhao et al. 2014). The policy design of the ETS pilots in China reflects the characteristics of the imperfect market and economic development in an emerging economy.

(1) Scope

The first thing of constructing an ETS is decide on what industries to involve. In total, energy and manufacture/industrial process are commonly covered by existing ETS, including China's ETS and EU ETS. EU ETS also covers aviation, while in China, covering aviation or transportation is at discussion stage for most pilots. China's ETS covers both direct emissions and indirect emissions[4]. For instance, Beijing and Shenzhen involve public buildings as participants in ETS. EU ETS, however, does not cover those indirect emission sources. One reason for this difference is that the indirect GHG emissions account for a large proportion of the total emissions in China. The other reason is that China's electricity price is regulated rather than determined by the market, which means that the cost change of electricity generation cannot be reflected in the electricity price.

(2) Cap setting

[4] Direct emissions refer to emissions from direct energy consumption, industrial processes and production. Indirect emissions refer to emissions from indirect energy consumption. Indirect emission sources can be public buildings, hotels, banks and so on.

The cap assigned to involved participants can be absolute caps or intensity-based caps. Absolute targets limit emission level to a pre-specified absolute quantity while intensity-based targets limit emission level to a pre-specified emission rate relative to input or output (Ellerman and Wing 2003). In practice, all seven ETS pilots in China assign intensity-based caps to participants compared to the use of absolute caps in EU ETS.

There are four tier intensity based emission reduction targets in China: country level, provincial level, city level and enterprise level. China set an emission intensity-based target for the country in its FYPs, and provinces and cities set their targets accordingly. Thereafter, each ETS pilot set emission caps for participating enterprises. China's GHG emissions have not reached its peak yet, while the country still keeps a rapid economic development. Setting intensity-based caps saves space for future economic growth in China. Besides, the intensity-based cap setting can make better adjustments for the emergence of new entrants and unexpected changes of emission reduction cost. However, as the cap setting allows rapid economic growth to be continue, its effectiveness on emission abatement has higher uncertainty than the absolute cap setting in a short term.

(3) Allowance allocation methods

Normally, there are two major approaches of allowance allocation, which are free allocation and auctioning. Auctioning is more appropriate when the carbon trading market becomes mature and participants are familiar with rules in the market, while free allocation can be applied at the initial stage of carbon trading (Zhao et al. 2014). The combination of free allocation and auctioning is prevalent across pilots. Auctioning has been used as a complementary allocation method in Guangdong, Shanghai and Shenzhen, and will be used in Beijing and Tianjin. Similarly, EU-ETS relied on free allocation and allocated a small portion of allowances by auctioning, but it is on a progress toward full auctioning. Another feature of

China ETS is that the regulations are on industry sectors and enterprises, different from the EU ETS that emphasizes regulations on installations.

(4) Allowance reserves for price containment

Reserving emission allowances for price containment and for the emerging new entrants is also a feature of China's ETS. The reserve mechanism has been used by Beijing, Guangdong, Hubei and Shenzhen. In these pilots, the reserve mechanism is combined with set price floors to abate price volatility. Some pilots, such as Shenzhen and Beijing, also set price ceilings to further stabilize the market. The reserves for price containment will be sold when the carbon price is too high and be bought back when the carbon price is too low.

(5) Market rules for allowance trading

In contrast with EU-ETS, China's ETS pilots allow only spot trading[5]. So, futures contracts are not applicable in China at present. Take Shenzhen as an example. At the beginning of its establishment, Shenzhen ETS employed fixed price trading[6], which gave participants more opportunity to express their preferences. But fixed price trading was criticized for time inefficient, low transaction amount and distorted price signal. Therefore, Shenzhen has changed the trading type to spot trading since 20th December 2013, which was supposed to operate more efficiently.

(6) Compliance calendar and penalties

The enforcement of assigned amount of emission allowances can be facilitated by penalties for non-compliance. Types of penalties can be stricter emission targets in the next compliance period, monetary fines on excess emissions, or both. EU ETS, Shenzhen ETS, Hubei ETS and Guangdong ETS use both types of penalties. In Phase II of EU ETS, non-compliant enterprises have to pay 100€ (about 143 $) penalty per ton of excess CO_2e emissions[7] and the over

---

[5] In the spot trading, a seller or a buyer just report his fixed price. When a potential buyer can accept the price or offer a higher price, the transaction can be reached.

[6] In the fixed price trading, a seller sets the fixed price and fixed amount of trading units to offer and a potential buyer sets the fixed price and fixed amount of trading units needed. One success transaction can be achieved when both the price and amount of trading units match.

[7] CO2 equivalent emissions

emissions would be deducted from the following compliance year's allowances. Shenzhen, Hubei and Guangdong ETS are similar to EU-ETS in using stricter emission allocation for non-compliance, but different from EU-ETS regarding the amount of monetary fines. In Shenzhen and Hubei, non-compliant enterprises should pay the penalty equal to three times the average market price for each ton of CO_2 emissions exceeding the limit, while Guangdong charges a total amount of up to 50000 ￥ (about 7900 $) for non-compliance. In Beijing and Shanghai, however, there are only monetary fines on non-compliance. Chongqing and Tianjin ETS set no monetary penalties for non-compliance at all, but disqualify non-compliant entities from associated subsidies or rewards for the next three years.

The compliances of regulated enterprises in any local ETS follow a specific calendar. At the beginning of year T in each ETS pilot, the regulated enterprises receive their allocations for year T. The regulated enterprises have to submit their emission reports to the regulator in March or the end of February, dates varying with pilots, and then ask a third party to verify the reports. In April, the regulated enterprises should submit the verified emission reports, and in June, they have to submit the allowances valid during year T-1 which should not go over the allocations for year T-1. So, the trading of emission allowances is relatively active between April and June of year T.

4 Method

4.1 Data

Carbon market (i.e. ETS market) data is collected from the website (www.tanpaifang.com) organized by Zhongke Carbon Information Technology Research Institute. The website was created in 2012, providing data, regulatory information and consultancy about ETS. Market data of China's piloting ETS that the website publicizes are daily carbon prices and daily trading volume. As China's ETS pilots allow for only spot trading, all price and transaction volume data are spot trading data. Market data of China's seven ETS markets can also be found from the website (www.chinacarbon.net.cn) organized by Climate Limited, which is a UN accredited online media company and a member of International Emissions Trading Association (IETA). Market data of China's ETS from the two sources are identical. This study collected the daily market data of the seven ETS pilots from their starting time points (see Table 1), to 30 June 2016, when valid allowances had been submitted for the recent compliance year (i.e.2015). The currency unit of all data is changed from RMB (￥) to US dollar ($), using the currency conversion rates provided by OECD. As the carbon price data are missing for some days, weekly carbon price data ($Price_t$, $/ton CO_2e) are generated for analysis. Further, a time-series variable of $lnReturn_t$ is generated for each pilot using the equation $\ln Return_t = \ln(Price_t/Price_{t-1})$.

On energy markets, the oil and coal price series are used. The currency unit is all converted to US dollar ($) as well. The oil price, *Brent* ($/barrel), is the weekly Europe Brent Spot Price for crude oil and petroleum products, published by US Energy Information Administration. The coal price is the domestic Bohai Rim 5500 kcal stream coal price ($Coal_t$, $/ton, weekly) based on the average price of 5500 kcal coal at Qinhuangdao, Tianjin, Caofeidian, Jingtang, Huanghua and Guotoujingtan ports. The data is published by Qinhuangdao Maritime Coal Market Co., Ltd[8].

4.2 Empirical analysis methods

Time series analysis techniques are applied to test the hypotheses. The Akaike Information Criterion (AIC) is used as the criteria for choosing the number of lags in all tests.

4.3.1 Testing for efficient market hypothesis

In its weak form, EMH assumes that, in an informationally efficient market, price changes are random and unforecastable. To test the hypothesis (Hypothesis 1), Augmented Dickey Fuller (ADF) tests were applied based on $\ln Return_t$ series to check the randomness of price returns.

[8] Data is available at: http://osc.cqcoal.com/ListInfo.jsp?id=V02&curPage=8.

$lnReturn_t$ data are preferred for EMH analysis compared to price data as $lnReturn_t$ data are analytically more tractable and more useful to investors (Mobarek and Keasey 2000). If $lnReturn_t$ series follow a random walk (a.k.a. having a unit root), it implies a weak-form market efficiency. If a random walk is not found, $lnReturn_t$ is predictable from the past returns, which can be the basis of profitable investment rule (Mobarek and Keasey 2000). ADF test was performed in three forms: random walk model with drift, random walk model with deterministic trend, and pure random walk model. The Philips-Perron (PP) test was also applied as a robustness check.

4.3.2 Short-and long-run dynamics between markets

To test Hypothesis 2 and 3, we used Engle-Granger Augmented Dickey-Fuller (EG-ADF) test based on natural logarithm price series. EG-ADF test for co-integration between X_t and Y_t included two steps. First, it estimates the coefficients of the regression $Y_t=a_0+a_1X_t+\varepsilon_t$ by OLS estimator. a_1 is the so-called co-integrating coefficient. When there is a significant autocorrelation issue in addition to possible heteroscedasticity, Newey–West estimator is used instead to produce consistent estimates. Second, it uses ADF test to test for the unit root of the residual series ε_t. If the hypothesis that u_t has a unit root is rejected, X_t and Y_t are co-integrated, and the stationary linear combination ($\varepsilon_t= Y_t - a_1X_t$) suggests a long-run equilibrium relationship. The EG-ADF test was run between every two local ETS market of China, using logarithm emission allowance price ($lnPrice_t$). We also used the same methods to identify the co-integration relationships between ETS markets and energy markets, on the basis of the logarithm coal price ($lnCoal_t$) and the logarithm oil price ($lnBrent_t$).

Further, we identified the co-integration relationships of multiple markets, using Johansen's multivariate test and VECM method. The Johansen's multivariate test could identify the co-integration ranks of multiple variables. Subsequently, based on the co-integration ranks, the Vector Error-Correction Model (VECM) could find the co-integration equations of the co-integrated variables. With the VECM technique, we analyzed the short-run and long-run dynamics of variables.

A simple VECM model can be displayed using the equations (1) - (2). The term $\varepsilon_t = Y_t - \theta X_t$ is the error correction term.

$$\Delta Y_t = \beta_{10} + \beta_{11}\Delta Y_{t-1} + \cdots + \beta_{1p}\Delta Y_{t-p} + \delta_{11}\Delta X_{t-1} + \cdots + \delta_{1p}\Delta X_{t-p} + \sigma_{11}(Y_{t-1} - \theta X_{t-1}) + u_{1t} \quad (1)$$
$$\Delta X_t = \beta_{20} + \beta_{21}\Delta Y_{t-1} + \cdots + \beta_{2p}\Delta Y_{t-p} + \delta_{21}\Delta X_{t-1} + \cdots + \delta_{2p}\Delta X_{t-p} + \sigma_{21}(Y_{t-1} - \theta X_{t-1}) + u_{2t} \quad (2)$$

4.3.3 Time series regressions and structural breaks

To further discuss the influence of energy price changes and structural breaks on carbon price changes, time series regressions were performed using the technique of adjusted Autoregressive Distributed Lag (ADL) model with multiple repressors. And, the regressions were estimated with the robust. If there is a significant serial correlation problem, the Newey-West heteroscedasticity-and-autocorrelation-consistent estimator should be used.

As shown in Figure 1, carbon price series in China have large fluctuations around week 26 (30 June-7 July), 2014, and some fluctuations around week 26 (29 June-7 July), 2015, both close to the due dates for submitting valid allowances. For instance, the carbon price of Beijing had a sudden spike around week 26 2014. However, Carbon price series in any ETS pilot of China do not have so obvious structural breaks as what happened in EU ETS. To test whether there are significant structural breaks over the two periods, the Wald likelihood ratio test has been run on the natural logarithm prices series. The tests indicate that, for all pilots except Chongqing and Hubei, there is a significant structural break over the week 26 2014. Chongqing ETS started from June 2014, so there are few observations before week 26, 2014. For Beijing, Guangdong and Hubei, $lnPrice_t$ also has a significant structural break over the week 26, 2015. In our regressions, we use two dummy variables, *Break14* and *Break15*, to define the two breaks. *Break14* has a value of 1 if it is after the week 26, 2014. Otherwise, *Break14* is 0. *Break15* has a value of 1 if it is after the week 26, 2015. Otherwise, its value is 0. So there are three sub-periods in the dataset, June 2013-June 2014 (1st Year), July 2014-June 2015 (2nd Year), and July 2015-June 2016 (3rd Year).

Therefore, the following specification is introduced:

$$\begin{aligned}\text{lnReturn}_{i,t} = {} & a_{i,0} + a_{i,1}(LD)lnReturn_{i,t} + a_{i,2}(LD)\text{ln}Brent_t + a_{i,3}(LD)lnCoal_t + a_{i,4}Break14 \\ & + a_{i,5}Break15 + a_{i,6}Break14 * \text{ln}Brent_t + a_{i,7}Break14 * \text{ln}Coal_t \\ & + a_{i,8}Break15 * \text{ln}Coal_t + a_{i,9}Break15 * lnCoal_t + \mu_{i,t}. \end{aligned} \tag{3}$$

In the equation, $lnReturn_{i,t}$ is the price return of emission allowance at time period t in the ETS pilot i. Price return series are used because they are stationary. L denotes the lag operator. D denotes the first difference. $\mu_{i,t}$ is the error term.

5 Results

5.1 Descriptive statistics and price volatility

The descriptive statistics are shown in Table 1. Shenzhen ETS and Beijing ETS had the highest carbon prices on average, which were 8.40 and 7.84 \$/ton CO_2e respectively, followed by Guangdong, 4.99 \$/ton CO_2e. Hubei, Tianjin and Shanghai had similar carbon prices on average, which were respectively 3.75, 3.95 and 4.00 \$/ton CO_2e. Chongqing had the lowest average carbon price, 3.32 \$/ton CO_2e. From Figure 1, we can see that there was a general decrease trend of carbon price over time in every ETS pilot. Take Shenzhen ETS as an example. Its carbon prices were at a level of more than 10 \$/ton CO_2e during June 2013 to June 2014. Then, the carbon price gradually decreased to about 5 \$/ton CO_2e by the end of 2014 since the submission of verified emissions in the first compliance year. From the end of 2014 to June 2016, the carbon price reached a relative stable status, ranging between 5-8 \$/tonCO_2e.

[Figure 1 here]

[Table 1 here]

The realized price volatility is analyzed by calculating the standard deviation of inter-day lnReturn_t series in order to measure the overll risk of the market. Overall, the ETS pilots in China all had a high price volatility, ranging from 0.02 to 0.13, which can be seen from Figure

2. As a contrast, the realized price volatility in EU ETS from 2008 to 2011 was about 0.024, calculated as the standard deviation of daily $lnReturn_t$ of carbon futures (Byun and Cho 2013). Full sample analysis show that, Shanghai ETS and Guangdong ETS exhibit the highest price volatility, which is about 0.10, followed by Tianjin (0.09) and Shenzhen (0.09). Hubei ETS, on the other hand, displays the lowest price volatility of 0.04. In each ETS pilot, the realized price volatility changes over different compliance years. For instance, carbon price of Beijing ETS had a relatively low volatility in the first two years, but experienced a much higher level of volatility in the third year. Chongqing, Hubei and Shanghai also had an increasing price volatility over time. Guangdong ETS had a highly volatile price changes (with a volatility as 0.13) in 2014-2015, which was twice the volatility level (0.05) in 2013-2014 but decreased to 0.08 in 2015-2016. Shenzhen ETS had a high price volatility level (0.12) in the first year, which significantly decreased in the second year but slightly increased again in the third year. The price volatility of Tianjin ETS changed in the same pattern.

[Figure 2 here]

5.2 Testing for efficient market hypothesis

Table 2 displays the unit test results of price returns ($lnReturn_t$) using ADF method. If the ADF test is significant, we reject the hypothesis that $lnReturn_t$ has a unit root and the EMH is violated. The tests were performed for the full period and the sub-periods. However, we can see from Table 2 that, the EMH is significantly rejected for all ETS pilots, except Tianjin ETS. Therefore, all the other six ETS markets were inefficient, no matter based on full period analysis or sub-period analysis.

Regarding Tianjin ETS, the full period analysis found that the market was significantly inefficient over the full sample period. The sub-period analysis then found the development of Tianjin ETS from an inefficient market to an efficient market. While $lnReturn_t$ did not follow a random walk in the first two years, a unit root of $lnReturn_t$ was found in the third year (July

2015-June 2016), implying a weak-form efficient market. However, the finding needs to be taken cautiously. In emerging and non-competitive markets, such as ETS markets, infrequent or “thin” trading can bias the result of EMH analysis (Montagnoli and de Vries 2010). Tianjin ETS only has about 110 enterprises regulated by ETS, and according to the trading volume data that we collected, Tianjin ETS had zero trading volume during 12% of the 131 weeks that we observed, which can be the evidence of infrequent trading to some extent.

[Table 2 here]

5.3 Analysis of short- and long-run causal effects

5.3.1 Relations between two markets

The results of co-integration tests are displayed in Table 3 and Table 4. Table 3 show the results of co-integration tests between two markets during the full sample period, using EG-ADF test. The test was performed only using logarithmic price series that are integrated of order one during the full sample period. $lnPrice_t$ of Beijing ETS ($lnBJPrice_t$) and that of Shenzhen ETS ($lnSZPrice_t$) are integrated of order zero. So, they are not involved in the co-integration tests. If two variables, X_t and Y_t, are co-integrated, their stationary linear combination, (Y_t -a_1X_t) implies a long-term equilibrium relationship between X_t and Y_t, with a_1 as the co-integrating coefficient. Table 4 show the identified co-integration relationships of multiple markets, using a combination of Johansen’s test and VECM method.

We can see from Table 3 that Hypothesis 2 does not hold for every two local ETS markets. Based on results of EG-ADF test, eight co-integration relationships were identified between two local ETS markets. There are respectively (1) the co-integration of $lnPrice_t$ series between Chongqing ETS and Guangdong ETS at 5% significance level, (2) the co-integration between Chongqing and Shanghai at 1% level, (3) the co-integration between Chongqing and Tianjin at 5% level, (4) the co-integration between Guangdong and Shanghai at 5% level, (5) the co-integration between Guangdong and Tianjin at 1% level, (6) the co-integration between

Shanghai and Hubei at 10% level, (7) the co-integration between Tianjin and Hubei at 1% level, and (8) the co-integration between Shanghai and Tianjin at 5% level.

When testing for the co-integrations between ETS market and energy markets, Hypothesis 3 does not hold for every pair of a ETS market and an energy market either. The results also suggest eight significant co-integration relationships. The $lnPrice_t$ series of Chongqing ETS ($lnCQPrice_t$) was found to be co-integrated with logarithmic coal price series ($lnCoal_t$) at 5% significance level and co-integrated with logarithmic oil price series ($lnBrent_t$) at 5% level. Also, the $lnPrice_t$ series of Guangdong ETS ($lnGDPrice_t$) was significantly co-integrated with $lnBrent_t$ at 5% level and co-integrated with $lnCoal_t$ at 10% level. Further, the logarithmic price series of Shanghai ETS ($lnSHPrice_t$) was found to be significantly co-integrated with $lnBrent_t$ and $lnCoal_t$, respectively. Similarly, Tianjin ETS ($lnTJPrice_t$) was significantly co-integrated with both $lnBrent_t$ and $lnCoal_t$.

[Table 3 here]

5.3.2 Relations of multiple markets

A co-integration relationship can also involve multiple markets. Table 4(1) displays the results of Johansen's test involving logarithmic price series of five ETS pilots and the two energy markets. So, the test identified three co-integration relationships at 5% significance level based on the full period analysis. The VECM method was employed subsequently to estimate the three co-integration equations, as shown in Table 4(2). The error correction terms, ε_{t1}, ε_{t2} and ε_{t3} are on the left side of the equations. So the identified co-integration equations are:

$$\varepsilon_{t1} = \mathrm{lnCQPrice}_t - 0.40\mathrm{lnSHPrice}_t - 0.71\mathrm{lnTJPrice}_t + 0.29\mathrm{lnCoal}_t - 1.08\mathrm{lnBrent}_t + 3.51 \tag{4}$$

$$\varepsilon_{t2} = \mathrm{lnGDPrice}_t + 0.77\mathrm{lnSHPrice}_t - 0.78\mathrm{lnTJPrice}_t - 3.42\mathrm{lnCoal}_t - 0.25\mathrm{lnBrent}_t + 14.67 \tag{5}$$

$$\varepsilon_{t3} = \mathrm{lnHBrice}_t + 0.02\mathrm{lnSHPrice}_t - 1.07\mathrm{lnTJPrice}_t + 2.32\mathrm{lnCoal}_t - 1.43\mathrm{lnBrent}_t - 3.80 \tag{6}$$

The coefficients on ε_{t1} in the equations of first-differenced logarithmic price *series* $D\_lnCQPrice_t$, $D\_lnGDPrice_t$, $D\_lnHBPrice_t$, $D\_lnSHPrice_t$, $D\_lnTJPrice_t$, D_lnCoal_t, and $D\_lnBrent_t$ can be shown in an adjustment matrix σ_1^T= *[0.003, -0.299**, 0.063, 0.229*, -0.177**, 0.041***, 0.142**]*[9]. The adjustment matrix for ε_{t2} and that for ε_{t3} are σ_2^T= *[-0.012***, -0.057, 0.046**, -0.090**, 0.057**, 0.006, 0.015]* and σ_3^T= *[-0.038***, 0.262***, -0.030, -0.278***, 0.159***, -0.037***, -0.064].*

[Table 4 here]

For the equation of ε_{t1}, the coefficient on $lnBrent_t$ is statistically significant, and so is the adjustment parameter on $D\_lnGDPrice_t$, $D\_lnSHPrice_t$, $D\_lnTJPrice_t$, and D_lnCoal_t. Therefore, $lnBrent_t$ respectively has a long-run equilibrium effect on $lnGDPrice_t$, $lnSHPrice_t$, $lnTJPrice_t$, and $lnCoal_t$.

For the equation of ε_{t2}, the coefficients on $lnCoal_t$ and $lnSHPrice_t$ are statistically significant, as are the adjustment parameters on $D\_lnCQPrice_t$, $D\_lnHBPrice_t$, $D\_lnSHPrice_t$, and $D\_lnTJPrice_t$. The significant adjustment parameters imply rapid adjustments toward equilibriums. So, $lnCoal_t$ and $lnSHPrice_t$ have long-run equilibrium effects respectively on $lnCQPrice_t$, on $lnHBPrice_t$, on $lnSHPrice_t$, and on $lnTJPrice_t$.

For the equation of ε_{t3}, the coefficient on $lnBrent_t$ is statistically significant at 1% level, and the coefficient on $lnTJPrice_t$ is weakly significant at 10% level. The adjustment parameters on $D\_lnCQPrice_t$, $D\_lnGDPrice_t$, $D\_lnSHPrice_t$, $D\_lnTJPrice_t$, and D_lnCoal_t are also significant, indicating rapid adjustments toward equilibriums. Thus, $lnBrent_t$ and $lnTJPrice_t$ have long-run equilibrium effects respectively on $lnCQPrice_t$, on $lnGDPrice_t$, on $lnSHPrice_t$, on $lnTJPrice_t$ and on $lnCoal_t$.

To sum up, the oil price has long-term equilibrium effects on the carbon prices of Chongqing ETS, Guangdong ETS, Hubei ETS, Shanghai ETS and Tianjin ETS; the coal price has a long-

[9] *, **, and *** denote significance at 1%, 5% and 10% levels

term equilibrium effect on carbon prices of Chongqing ETS, Hubei ETS, Shanghai ETS and Tianjin ETS. Regarding long-term effects between ETS markets, the carbon price of Shanghai ETS exhibits long-term equilibrium effects on the carbon prices of Chongqing ETS, Hubei ETS, Shanghai ETS and Tianjin ETS. Also, the carbon price of Tianjin ETS exhibits the weakly significant long-term equilibrium effects on the carbon prices of Chongqing ETS, Guangdong ETS, Shanghai ETS, and Tianjin ETS.

Table 4(3) display the results of joint significance tests of short-run coefficients of VECM, which provide evidence for the short-run effect/granger causality between price changes. In the equation of $lnSHPrice_t$, the joint F-test of the coefficients on all values of $lnBrent_t$ is significant at 5% level, while in the equation of $lnBrent_t$, the joint F-test of the coefficients on all values of $lnSHPrice_t$ is not significant. This suggests a unidirectional short-run granger causality from oil price to Shanghai carbon price. Also, the values of $lnBrent_t$ are jointly significant in the equation of $lnCQPrice_t$, whereas the values of $lnCQPrice_t$ are not jointly significant in the equation of $lnBrent_t$, implying a unidirectional short-run granger causality from oil price to Chongqing carbon price.

Regarding short-run dynamics between two ETS pilots, the values of $lnSHPrice_t$ are jointly significant in the equation of $lnHBPrice_t$, but the values of $lnHBPrice_t$ are not jointly significant. So, the Shanghai carbon price has a short-run effect on the Hubei carbon price, but the reverse is not true. Also, the Shanghai carbon price has a short-run unidirectional effect on the Tianjin carbon price. In addition, there is a short-run unidirectional granger causality from the Hubei carbon price to the Tianjin carbon price.

5.4 Regression analysis and structural breaks

Table 5 displays the regressions of carbon price returns on energy price returns and structural break dummies. All logarithmic price return series in the regressions are stationary. The regressions are estimated using the robust estimator rather than Newey-West estimator as there is no significant serial correlation problem. Joint F-tests are used to test the joint significance of coefficients on all values of a variable, and the results can be found from the last four rows of Table 5. The joint F- test results are mainly commented.

Regarding influence of energy price change on carbon price change, the joint F-tests show that $D\_lnBrent_t$ is weakly significant in the equation of Beijing's carbon price return $lnBJReturn_t$, but it is not significant in other equations. D_lnCoal_t exhibits a significant joint effect on Guangdong's carbon price return $lnGDReturn_t$, and a significant joint effect on Hubei's carbon price return $lnHBReturn_t$.

In terms of influences of structural break dummies, *Break14* has a negative coefficient at 10% significance level in the equation of $lnBJReturn_t$, implying a weakly significant decrease of carbon price return after the June 2014 break. But, the joint F-test of *Break14* and its interaction terms is not statistically significant. In the equation of $lnGDReturn_t$, the coefficient on *Break14* is negative and significant at 1% level, suggesting a significant collapse of carbon price return after the June 2014 break as well. And, the joint F-test of coefficients on all terms of Break14 is jointly significant at 5% level. *Break15* has a significant yet positive coefficient in $lnGDReturn_t$ equation, indicating a sudden increase of carbon price return after the June 2015 break in Guangdong. The joint F-test of *Break15*, however, is not significant. In the equation of $lnSHReturn_t$, the coefficient on *Break14* is negative and weakly significant, so is the joint F-test of *Break14* and its interaction terms. In addition, the joint F-tests of all terms of *Break15* show that *Break15* has a joint significant effect on $lnBJReturn_t$ at 10% level, and also a joint significant effect on $lnHBReturn_t$. In short, based on joint F-tests, Beijing and Hubei respectively have a significant structural change in carbon price return before and after the end of June 2014, while Guangdong and Shanghai respectively have a significant structural break in the carbon price return over the end of June 2015.

[Table 5 here]

6 Discussion and concluding remarks

This study contributes to the existing literature on ETS by adding empirical evidence in the context of China. The particular literature about EU ETS frequently discuss market efficiency, price volatility, and price drivers that focus on the influence of energy markets. The econometric analysis of the weekly spot carbon price conducted in this study compares carbon pricing in the seven ETS pilots of China, examines the efficient market hypothesis, and evaluates impacts of two types of price drivers identified in EU ETS which are energy prices and institutional design issues.

The three main findings in this study are summarized as follows. First, full sample analysis shows that all local ETS markets in China are not informationally efficient during 2013-2016 according to the weak-form EMH. The result is consistent with what happened to EU ETS in its early days, as Montagnoli and Vries (2010) found that the EU ETS was also inefficient in Phase I. The policy design and implementation of the local ETS pilots are not so transparent in China. And the trading volumes are generally at a low level and unstable, as the market liquidity is poor and the derivatives trading is off-limits.

The second main finding is that carbon prices between different ETS markets are co-integrated, but this is not true for every two ETS markets in China. Co-integration relationships of carbon prices exist (1) between Guangdong and Chongqing, (2) between Guangdong and Shanghai, (3) between Guangdong and Tianjin, (4) between Shanghai and Chongqing, (5) between Shanghai and Tianjin, (6) between Shanghai and Hubei, (7) between Tianjin and Chongqing, and (8) between Tianjin and Hubei. So, Tianjin carbon price is co-integrated with carbon prices of all the other ETS pilots, except Beijing and Shenzhen. VECM analysis confirmed that Tianjin carbon price has a weakly significant long-term equilibrium effect respectively on carbon prices of Guangdong, Chongqing and Shanghai; Shanghai carbon price has a significant long-run equilibrium effect respectively on carbon prices of Chongqing, Hubei and Tianjin.

The existence of these co-integration relationships between local ETS markets in China may be good for linking different local ETS markets.

Third, energy prices have both short- and long-run dynamic effects on carbon prices of the ETS markets in China. In particular, the EG-ADF analysis found that coal price is respectively co-integrated with carbon prices of Guangdong, Chongqing, Shanghai, and Tianjin; oil price is respectively co-integrated with the carbon prices of Guangdong, Chongqing, Shanghai, and Tianjin. Further, the Johansen's multivariate test and VECM analysis confirmed that oil price has a significant long-run equilibrium effect respectively on carbon prices of Guangdong, Chongqing, Shanghai and Tianjin, so does coal price. In addition, the analysis of short-run dynamics found that there are unidirectional short-run granger causal relationships from oil price to Chongqing carbon price, and from oil price to Shanghai carbon price. Besides, Shanghai carbon price has a unidirectional short-run granger causal effect on Hubei carbon price and Tianjin carbon price, respectively; Hubei carbon price has a unidirectional short-run effect on Tianjin carbon price. These findings have implications for the regulators of ETS markets in China who need to concern about the source of price volatility from energy price fluctuations.

Concerning "compliance breaks", we also analyzed two structural break dummies surrounding the two dates, 30 June 2014 and 30 June 2015, when the regulated entities have to submit the valid allowances of the last year to regulators. Regression analysis using adjusted multivariate ADL model found that the carbon price returns of Beijing ETS and Hubei ETS have significant structural changes around June 2014, whereas the carbon price returns of Guangdong ETS and Shanghai ETS have significant structural breaks around June 2015. This finding serves as an evidence that carbon prices are driven by institutional decisions in those pilots.

Descriptively, the carbon prices in each ETS pilot of China are far less than the ideal prices that can cause substantial low-carbon actions. According to a government official in China's

NDRC, the carbon price should ideally be 30-45 \$/ton in order to motivate enterprises to take strategic actions[10]. However, even in Shenzhen, the highest carbon price was less than 20\$/ton CO_2e over the history of price development. Regarding Shanghai ETS, its minimum carbon price was only 0.68\$/ton CO_2e, which provided poor incentive for emitters to invest in low-carbon technologies. In that case, even if an enterprise reduces emissions that are equivalent to 10000ton emission allowance by introducing low-carbon technologies, which is hard and costly, the enterprise can only earn 6800\$, which is a tiny number to a middle-to-large enterprise. What's worse, the volatility of carbon prices in China is generally high and varies with different ETS pilots. As a comparison, the price of carbon futures in EU ETS during Phase II (2008-2012) was about 23.64 \$/ton CO_2e on average (Daskalakis 2013). And in particular, the carbon futures price was 25.49 \$/ton CO_2e in December 2009, 23.04 \$/ton CO_2e in December 2010, 23.43 \$/ton CO_2e in December 2011 and 22.57 \$/ton CO_2e in December 2012 (Daskalakis 2013). Nonetheless, the carbon price in EU ETS decreases to a low level in Phase III (2013-2020). According to World Bank (2015; 2016), the carbon price in EU ETS was only 8\$/ton CO_2e or so in April 2015, and 6\$/ton CO_2e or so in April 2016, which were quite similar to the carbon price in Shenzhen ETS during the same time. Given the low carbon prices, the ETS has to be complemented with other policy instruments to motivate significant low-carbon actions.

[10] http://www.tanpaifang.com/tanjiaoyi/2016/0620/53811.html

References

Alberola, Emilie, Julien Chevallier, and Benoît Chèze. 2008. "Price Drivers and Structural Breaks in European Carbon Prices 2005-2007." *Energy Policy* 36 (2): 787–97. doi:10.1016/j.enpol.2007.10.029.

Bertoldi, Paolo, and Silvia Rezessy. 2009. "Voluntary Agreements for Energy Efficiency: Review and Results of European Experiences." *Energy & Environment* 18 (1): 37–73. doi:10.1260/095830507780157258.

Byun, Suk Joon, and Hangjun Cho. 2013. "Forecasting Carbon Futures Volatility Using GARCH Models with Energy Volatilities." *Energy Economics* 40. Elsevier B.V.: 207–21. doi:10.1016/j.eneco.2013.06.017.

Chevallier, Julien. 2012. *Econometric Analysis of Carbon Markets: The European Union Emissions Trading Scheme and The Clean Development Mechanism*. Dordrecht; New York: Springer. doi:10.1007/978-94-007-2412-9.

Daskalakis, George. 2013. "On the Efficiency of the European Carbon Market: New Evidence from Phase II." *Energy Policy* 54: 369–75. doi:10.1016/j.enpol.2012.11.055.

de Leon, Peter. 1992. "Policy Formulation: Where Ignorant Armies Clash by Night." *Review of Policy Research* 11 (3–4): 389–405. doi:10.1111/j.1541-1338.1992.tb00480.x.

Ellerman, A. Denny, and Ian Sue Wing. 2003. "Absolute versus Intensity-Based Emission Caps." *Climate Policy* 3 (SUPP 2): S7–20. doi:10.1016/j.clipol.2003.09.013.

Grubb, Michael, Tim Laing, Thomas Counsell, and Catherine Willan. 2011. "Global Carbon Mechanisms: Lessons and Implications." *Climatic Change* 104 (3). Springer: 539–73.

Hintermann, Beat. 2010. "Allowance Price Drivers in The First Phase of The EU ETS." *Journal of Environmental Economics and Management* 59 (1): 43–56.

Howlett, Michael, and Raul Lejano. 2016. "Tales from the Crypt: The Rise and Fall (and Rebirth?) Of Policy Design." *Administration & Society* 45 (3): 356–80. doi:10.1177/0095399712459725.

Knill, Christoph, and Duncan Liefferink. 2007. "Taking Stock: The Environmental Problem-Solving Capacity of the EU." In *Environmental Politics in the European Union: Policy-Making, Implementation and Patterns of Multi-Level Governance*, edited by Christoph Knill and Duncan Liefferink, 1–13. Manchester: Manchester University Press. doi:10.7228/manchester/9780719075803.003.0018.

Mobarek, Asma, and K Keasey. 2000. "Weak-Form Market Efficiency of an Emerging Market: Evidence from Dhaka Stock Market of Bangladesh." In *ENBS Conference*, 1–30. Oslo, Norway. http://e-m-h.org/MoKe00.pdf.

Montagnoli, Alberto, and Frans P. de Vries. 2010. "Carbon Trading Thickness and Market Efficiency." *Energy Economics* 32 (6): 1331–36. doi:10.1016/j.eneco.2010.04.001.

National Development and Reform Commission (NDRC). 2015. "Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions (INDCs). Submitted to UNFCCC." http://www4.unfccc.int/submissions/indc/Submission Pages/submissions.aspx. .

Olivier, Jos G.J., Greet Janssens-Maenhout, Marilena Muntean, and Jeroen A.H.W. Peters. 2015. "Trends in Global CO2 Emissions: 2015 Report." *PBL Netherlands Environmental Assessment Agency & European Commission's Joint Research Centre (JRC)*. The Hague, The Netherlands; Ispra, Italy.

Reboredo, Juan C. 2014. "Volatility Spillovers between the Oil Market and the European Union Carbon Emission Market." *Economic Modelling* 36: 229–34. doi:10.1016/j.econmod.2013.09.039.

Stavins, Robert N. 1995. "Transaction Costs and Tradeable Permits." *Journal of Environmental Economics and Management* 29 (2). Elsevier: 133–48.

Wang, Qiang, and Xi Chen. 2015. “Energy Policies for Managing China’s Carbon Emission.” *Renewable and Sustainable Energy Reviews* 50: 470–79. doi:10.1016/j.rser.2015.05.033.

Weaver, R Kent. 2010. “But Will It Work? Implementation Analysis to Improve Government Performance.” *Governance Studies at Brookings*, no. 32: 1–17.

World Bank. 2015. *Carbon Pricing Watch 2015*. Washington, D.C., USA: World Bank. doi:10.1596/978-1-4648-0268-3.

———. 2016. *Carbon Pricing Watch 2016*. Washington, D.C., USA: World Bank. doi:10.1596/978-1-4648-0268-3.

Wurzel, K.W. Rüdiger, R. Anthony Zito, and J. Andrew Jordan. 2013. “Governing by Policy Instruments : Theories and Analytical Concepts.” In *Environmental Governance in Europe A Comparative Analysis of New Environmental Policy Instruments*, edited by K.W. Rüdiger Wurzel, R. Anthony Zito, and J. Andrew Jordan, 23–45. Cheltenham, UK: Edward Elgar Publishing, Inc.

Zhao, Xikang, Yunmin Zeng, Lijuan Wang, Baoya Shi, Dalei Wu, and Hui Long. 2014. “Localization Reform of Carbon Emissions Trading Mechanism in China.” *Meteorological and Environmental Research* 5 (6). Wu Chu (USA-China) Science and Culture Media Corporation: 35.

Tables and Figures

Table 1 Descriptive statistics

/	Market	Full period From	Obs.	Mean	Std. Dev.	Min	Max	P(Skew.)	P(Kurt.)	adj Chi2
$Price_t$	BJ	28-Nov-13	135	7.84	1.27	5.34	12.51	0.04	0.01	9.34***
	CQ	19-Jun-14	107	3.32	1.44	1.51	5.29	0.74	--	.
	GD	16-Dec-13	132	4.99	3.19	1.36	12.05	0.00	0.00	21.75***
	HB	2-Apr-14	118	3.72	0.46	2.19	4.40	0.00	0.00	34.38***
	SH	26-Nov-13	132	4.00	2.20	0.68	7.81	0.87	0.00	.
	SZ	18-Jun-13	158	8.40	2.73	4.68	18.36	0.00	0.95	13.63***
	TJ	26-Dec-13	131	3.95	0.91	1.52	7.42	0.00	0.00	19.92***
$Brent_t$	Europe	18-Jun-13	158	75.89	29.64	27.76	116.03	0.99	--	--
$Coal_t$	China, Qinhuangdao	18-Jun-13	158	76.22	13.03	55.84	101.84	0.69	0.00	--
$lnReturn_t$	BJ	28-Nov-13	134	0.00	0.07	-0.21	0.22	0.01	0.00	18.42***
	CQ	19-Jun-14	106	-0.01	0.05	-0.30	0.10	0.00	0.00	73.47***
	GD	16-Dec-13	131	-0.01	0.10	-0.31	0.29	0.84	0.00	7.45**
	HB	2-Apr-14	117	0.00	0.04	-0.18	0.15	0.37	0.00	14.97***
	SH	26-Nov-13	131	-0.01	0.10	-0.36	0.27	0.31	0.00	10.29***
	SZ	18-Jun-13	157	0.00	0.09	-0.27	0.42	0.00	0.00	30.69***
	TJ	26-Dec-13	130	-0.01	0.09	-0.54	0.29	0.00	0.00	40.02***
$D.lnBrent_t$	Europe	18-Jun-13	157	0.00	0.04	-0.16	0.16	0.15	0.00	13.88***
$D.lnCoal_t$	China, Qinhuangdao	18-Jun-13	157	0.00	0.01	-0.04	0.03	0.80	0.00	9.44***

Note: Full sample period started from the first operation date of the ETS pilots till 30 June 2016 when the regulated entities submitted the valid allowances of 2015 to the regulators. "*BJ*" is short for Beijing ETS, "*CQ*" for Chongqing ETS, "*GD*" for Guangdong ETS, "*HB*" for Hubei ETS, "*SH*" for Shanghai ETS, "*SZ*" for Shenzhen ETS, and "*TJ*" for Tianjin ETS. "*Std. Dev.*" indicates standard deviation; "*Obs.*" indicates the number of observations. $Price_t$ refers to a time-series variable of weekly carbon prices. $Brent_t$ refers to the Europe Brent Spot Price for crude oil and petroleum products. $Coal_t$ refers to Qinhuangdao 5500kcal/kg steam coal price in China. $lnReturn_t$ refers to the logarithmic form of price returns. $lnReturn_t = \ln(Price_t/Price_{t-1})$. $D.lnBrent_t$ and $D.lnCoal_t$ are respectively first logarithm differenced oil price series and coal price series, indicating oil price returns and coal price returns. Pr(Skew.), *Pr(Kurt.)* and *adj Chi2* display the results of Skewness-Kurtosis tests (sktest) in Stata. *Skew.* denotes skewness, and *Kurt.* denotes kurtosis. The null hypothesis of *sktest* is that the data follow normal distribution. The statistic of sktest is adjusted Chi squares (*adj Chi2*). *** and ** denote significance at 1% and 5% levels. "--" denotes the statistics are not available due to the characteristics of the original data.

Table 2 Test for unit root of price returns

Price return		Obs	ADF, simple	PP, simple	ADF, with trend	PP, with trend	ADF, with drift	Integ.Order
			Z(t)	Z(t)	Z(t)	Z(t)	Z(t)	
$lnBJReturn_t$	Full period	134	-7.176***	-10.602***	-7.152***	-10.556***	-7.176***	I(0)
	1st Year	30	-0.559	-3.576***	-0.492	-3.965*	-0.559	I(1)
	2nd Year	52	-5.267***	-5.659***	-5.135***	-5.532***	-5.267***	I(0)
	3rd Year	52	-5.196***	-7.118***	-5.140***	-7.024***	-5.196***	I(0)
$lnCQReturn_t$	Full period	106	-6.607***	-7.872***	-6.587***	-7.846***	-6.607***	I(1)
	2nd Year	52	-4.023***	-5.286***	-4.617***	-5.821***	-4.023***	I(1)
	3rd Year	52	-4.869***	-5.602***	-4.848***	-5.568***	-4.869***	I(0)
$lnGDReturn_t$	Full period	131	-6.760***	-9.801***	-6.724***	-9.761***	-6.760***	I(1)
	1st Year	27	-4.564***	-6.215***	-4.536***	-6.098***	-4.564***	I(0)
	2nd Year	52	-4.297***	-5.408***	-4.296***	-5.346***	-4.297***	I(0)
	3rd Year	52	-5.560***	-8.015***	-5.956***	-8.380***	-5.560***	I(1)
$lnHBReturn_t$	Full period	117	-8.308***	-13.550***	-8.407***	-13. 628***	-8.308***	I(1)
	1st Year	13	-3.046**	-4.393***	-2.871	-4.284***	-3.046***	I(0)
	2nd Year	52	-5.561***	-8.194***	-5.505***	-8.113***	-5.561***	I(0)
	3rd Year	52	-5.656***	-9.433***	-5.690***	-9.444***	-5.656***	I(1)
$lnSHReturn_t$	Full period	131	-6.696***	-9.781***	-6.709***	-9.769***	-6.696***	I(1)
	1st Year	27	-4.132***	-4.541***	-4.728***	-4.755***	-4.132***	I(0)
	2nd Year	52	-5.664***	-7.799***	-5.826***	-7.864***	-5.664***	I(1)
	3rd Year	52	-4.280***	-4.976***	-4.259***	-4.984***	-4.280***	I(0)
$lnSZReturn_t$	Full period	158	-9.572***	-12.078***	-9.697***	-12.153***	-9.572***	I(0)
	1st Year	54	-5.790***	-6.280***	-6.345***	-6.570***	-5.790***	I(0)
	2nd Year	52	-5.769***	-7.960***	-5.882***	-7.995***	-5.769***	I(0)
	3rd Year	52	-4.971***	-8.169***	-4.936***	-8.101***	-4.971***	I(0)
$lnTJReturn_t$	Full period	130	-5.669***	-6.477 ***	-5.712**	-6.509***	-5.669***	I(1)
	1st Year	26	-3.990***	-3.868***	-3.927**	-3.755**	-3.990***	I(0)
	2nd Year	52	-3.191**	-3.770***	-3.171*	-3.708**	-3.191***	I(0)
	3rd Year	52	1.151	-2.321	0.241	-3.039	1.151	I(1)

Note: $lnReturn_t = ln(Price_t/Price_{t-1})$, denoting the price returns of carbon emission allowance. "BJ" is short for Beijing ETS, "CQ" for Chongqing ETS, "GD" for Guangdong ETS, "HB" for Hubei ETS, "SH" for Shanghai ETS, "SZ" for Shenzhen ETS, and "TJ" for Tianjin ETS. "Obs." indicates the number of observations. Augmented Dickey–Fuller (ADF) unit-root tests were performed with time trend, with drift, without time trend or drift. Phillips–Perron (PP) unit root tests were performed with and without time trend. "Z(t)" refers to the statistic of ADF or PP unit root test. *, ** and *** denote significance at 1%, 5% and 10% levels. Full sample period started from the first operation date of the ETS pilots till 30 June 2016. "1st Year" refers to the period from June 2013 to 30 June 2014. "2nd Year" refers to the period during July 2014-June 2015. "3rd Year" refers to the period during July 2015-June 2016. The lag options for the tests are selected based on AIC, but the lags are not presented to simplify the exposition. In addition, tests for unit roots of logarithm prices were performed to find the integration order of the logarithm prices, and "*Integ.Order*" reports the integration order accordingly.

Table 3 Co-integration relationships of prices between two markets

Logarithm Price		EG-ADF test		
		ADF test of residuals	Test statistic	Co-integrated?
ETS market vs. ETS market	$lnCQPrice_t$ vs. $lnGDPrice_t$	ADF, drift	-2.27**	Yes
	$lnCQPrice_t$ vs. $lnHBPrice_t$	ADF, drift	-1.16	No
	$lnCQPrice_t$ vs. $lnSHPrice_t$	ADF, drift	-3.16***	Yes
	$lnCQPrice_t$ vs. $lnTJPrice_t$	ADF, drift	-1.87**	Yes
	$lnGDPrice_t$ vs. $lnHBPrice_t$	ADF, drift	-0.97	No
	$lnGDPrice_t$ vs. $lnSHPrice_t$	ADF, drift	-2.19**	Yes
	$lnGDPrice_t$ vs. $lnTJPrice_t$	ADF, drift	-2.65***	Yes
	$lnSHPrice_t$ vs. $lnHBPrice_t$	ADF, drift	-1.63*	Yes
	$lnTJPrice_t$ vs. $lnHBPrice_t$	ADF, drift	-2.38***	Yes
	$lnSHPrice_t$ vs. $lnTJPrice_t$	ADF, drift	-2.24**	Yes
ETS market vs. Energy market	$lnCQPrice_t$ vs. $lnCoal_t$	ADF, drift	-2.00**	Yes
	$lnGDPrice_t$ vs. $lnCoal_t$	ADF, drift	-1.33*	Yes
	$lnHBPrice_t$ vs. $lnCoal_t$	ADF, drift	-0.46	No
	$lnSHPrice_t$ vs. $lnCoal_t$	ADF, drift	-2.63***	Yes
	$lnTJPrice_t$ vs. $lnCoal_t$	ADF, drift	-2.29**	Yes
	$lnCQPrice_t$ vs. $lnBrent_t$	ADF, drift	-1.87**	Yes
	$lnGDPrice_t$ vs. $lnBrent_t$	ADF, drift	-1.84**	Yes
	$lnHBPrice_t$ vs. $lnBrent_t$	ADF, drift	-0.37	No
	$lnSHPrice_t$ vs. $lnBrent_t$	ADF, drift	-1.69**	Yes
	$lnTJPrice_t$ vs. $lnBrent_t$	ADF, drift	-1.89**	Yes

Note: EG-ADF test was used. The test was performed only if the logarithm price series are integrated of order one. The tests were run between $lnPrice_t$ series of every two ETS pilots, between coal price ($lnCoal_t$) and $lnPrice_t$, between oil price ($lnBrent_t$) and $lnPrice_t$. The integration order of $lnPrice_t$ can be seen in Table 2. "BJ" is short for Beijing ETS, "CQ" for Chongqing ETS, "GD" for Guangdong ETS, "HB" for Hubei ETS, "SH" for Shanghai ETS, "SZ" for Shenzhen ETS, and "TJ" for Tianjin ETS. *, **, and *** denote significance at 1%, 5% and10% level. Full sample period started from the first operation date of the ETS pilots till 30 June 2016. For EG-ADF tests, the test procedure and test statistics of ADF tests of residuals are reported. The value for "Co-integrated?" is based on 5% significance level. That is, if ADF tests of residuals are significant, variables are considered as being co-integrated.

Table 4 Co-integration relationships of prices among multiple markets

(1) Johansen's test for co-integration ranks

Vars.	$lnCQPrice_t$, $lnGDPrice_t$, $lnHBPrice_t$, $lnSHPrice_t$, $lnTJPrice_t$, $lnCoal_t$, $lnBrent_t$			
Hypothesis	5% Critical value	Johansen stat.	Lags	Obs.
H0:r=2;H1:r>=3	68.72**	68.52	6	101
H0:r=3;H1:r>=4	43.01	47.21		

(2) Identified co-integration equations based on VECEM method

Vars.		$lnCQPrice_t$	$lnGDPrice_t$	$lnHBPrice_t$	$lnSHPrice_t$	$lnTJPrice_t$	$lnCoal_t$	$lnBrent_t$	Cons.
Equations	(1) ε_{t1}	1			-0.40	-0.71	0.29	-1.08***	3.51
	(2) ε_{t2}		1		0.77**	-0.78	-3.42**	-0.25	14.67
	(3) ε_{t3}			1	0.02	-1.07*	2.32	-1.43***	-3.80

(3) Short-run effects based on VECM method

Joint F-test	$D\_lnCQPrice_t$	$D\_lnGDPrice_t$	$D\_lnHBPrice_t$	$D\_lnSHPrice_t$	$D\_lnTJPrice_t$	D_lnCoal_t	$D\_lnBrent_t$
	Joint F-stat	Joint F-stat	Joint F-stat	Joint F-stat	Joint F-stat	Joint F-stat	Joint F-stat
$D\_lnCQPrice_t$	9.61*	6.01	3.64	5.64	3.01	5.44	3.12
$D\_lnGDPrice_t$	4.35	10.83*	2.44	7.17	2.79	8.42	5.48
$D\_lnHBPrice_t$	2.70	8.81	9.04	7.83	18.97***	5.41	1.85
$D\_lnSHPrice_t$	2.17	2.42	14.15**	5.98	21.44***	10.60*	8.12
$D\_lnTJPrice_t$	4.44	8.53	6.63	3.39	30.89	3.62	2.46
D_lnCoal_t	3.67	8.49	3.27	7.47	7.61	10.29*	6.21
$D\_lnBrent_t$	12.98**	3.23	7.03	15.12***	4.76	9.96*	7.24

Note: Logarithm prices ($lnPrice_t$) of each ETS market, coal price in its logarithmic form ($lnCoal_t$) and oil price in its logarithmic form ($lnBrent_t$) were used for a Johansen's co-integration test. Table 4(1) displays the result of the Johansen's test, which indicate that the co-integration rank (r) is three at 5% significance level. Table 4(2) displays the identified co-integration equations based on VECM method using 6 lags. On the left side of each equation is the error correction term (ε_t). Table 4(3) displays results of the joint F-tests following VECM analysis, which indicate the short-run effects. The tests and analyses were performed for the full sample period started from the first operation date of the ETS pilots till 30 June 2016. "Obs." indicates the number of observations. "BJ" is short for Beijing ETS, "CQ" for Chongqing ETS, "GD" for Guangdong ETS, "HB" for Hubei ETS, "SH" for Shanghai ETS, and "TJ" for Tianjin ETS. *, ** and *** denote significance at 1%, 5% and 10% levels. The lag options for the tests are selected based on AIC. "r" refers to co-integration rank. "D" denotes the first difference. "Cons." denotes constant terms. "Equ." refers to co-integration equation.

Table 5 ADL regression with multiple predictors, Full period

	$lnReturn_t$						
	BJ	CQ	GD	HB	SH	SZ	TJ
	Eq.1	Eq.2	Eq.3	Eq.4	Eq.5	Eq.6	Eq.7
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
L1. $lnReturn_t$	0.091	0.252*	0.009	-0.284*	0.141	0.006	0.353***
	(0.099)	(0.130)	(0.082)	(0.167)	(0.145)	(0.130)	(0.122)
L2.$lnReturn_t$	-0.313*	-0.051	-0.187**	-0.050	-0.207*	-0.138*	-0.100
	(0.117)	(0.050)	(0.091)	(0.182)	(0.116)	(0.076)	(0.137)
L3.$lnReturn_t$	0.107	0.007	-0.274***	-0.161	-0.057	-0.036	-0.162
	(0.122)	(0.050)	(0.094)	(0.161)	(0.086)	(0.085)	(0.144)
D_$lnBrent_t$	-0.173	0.163	0.492	-0.688**	-1.252	1.021	2.619
	(0.745)	(0.193)	(1.295)	(0.307)	(1.269)	(0.876)	(2.202)
L1D_$lnBrent_t$	0.258	-0.207	0.001	-0.041	-0.085	0.172	0.049
	(0.139)*	(0.129)	(0.172)	(0.104)	(0.219)	(0.146)	(0.129)
D_$lnCoal_t$	-0.196	0.558	-0.378	-1.234**	-1.347	0.114	-0.422
	(1.108)	(0.612)	(1.588)	(0.621)	(1.733)	(1.222)	(2.372)
L1D_$lnCoal_t$	-0.374	-0.156	-1.386	-0.203	-1.374	-0.606	-0.612
	(0.347)	(0.313)	(1.227)	(0.590)	(0.910)	(0.916)	(0.729)
L2D_$lnCoal_t$	0.330	-0.225	2.599***	0.191	1.406	-0.895	0.927
	(0.459)	(0.519)	(0.963)	(0.338)	(1.192)	(0.727)	(0.912)
Break14	-0.015*		-0.053***	0.008	-0.034*	-0.029	-0.003
	(0.009)		(0.019)	(0.007)	(0.019)	(0.020)	(0.027)
Break15	0.016	-0.0004	0.034**	-0.011	0.003	0.013	-0.004
	(0.013)	(0.009)	(0.017)	(0.008)	(0.024)	(0.016)	(0.017)
Break14*D_$lnBrent_t$	-0.070		-0.527	0.587*	1.625	-1.159	-2.598
	(0.754)		(1.415)	(0.322)	(1.324)	(0.898)	(2.210)
Break14*D_$lnCoal_t$	0.305		-3.784**	0.646	1.419	0.303	0.217
	(1.037)		(1.848)	(0.688)	(1.859)	(1.385)	(2.483)
Break15*D_$lnBrent_t$	0.486	-0.226	-0.092	-0.161	-0.543	0.086	-0.198
	(0.208)**	(0.212)	(0.545)	(0.142)	(0.458)	(0.297)	(0.197)
Break15*D_$lnCoal_t$	-0.945	0.347	0.734	1.528**	1.369	-0.779	-5.098
	(1.517)	(1.098)	(2.089)	(0.673)	(1.584)	(1.318)	(3.336)
Constant	0.005	-0.009	0.004	-0.010*	0.016	0.014	-0.004
	(0.006)	(0.006)	(0.015)	(0.005)	(0.010)	(0.017)	(0.026)
Obs.	131	105	128	114	128	154	127
R-squ.	0.181	0.143	0.266	0.166	0.102	0.068	0.255
F-stat.	1.500	1.160	3.160	2.390	1.170	0.800	1.610
Prob>F	0.123	0.329	0.000	0.007	0.308	0.665	0.087
Durbin's alternative test	0.357	0.022	0.594	0.086	1.357	2.064	1.144
BG LM test	0.406	0.025	0.675	0.100	1.533	2.269	1.296
Procedure	ADL, robust	ADL, robust	ADL, robust	ADL, robust	ADL, robust	ADL, robust	ADL, robust
Joint F-stat of Break14	1.290		3.270**	1.430	2.200*	1.760	0.640
Joint F-stat of Break15	2.310*	0.910	1.380	2.450*	0.820	0.450	1.240
Joint F-stat of D_$lnBrent_t$	2.000*	1.820	0.090	1.350	0.830	0.930	0.960
Joint F-stat of D_$lnCoal_t$	0.550	0.260	4.190***	3.000**	1.080	0.980	1.140

Note: Adjusted ADL model with multiple repressor is employed, and the regression is performed with the robust estimator when there is no significant serial correlation problem. Otherwise, the Newey- West heteroscedasticity-and-autocorrelation-consistent estimator should be used. For each ETS pilot, the price return ($lnReturn_t$) of carbon emission allowance is regressed on its lags, the logarithm difference of oil price (*D_lnBrent*$_t$) and its lags, the logarithm difference of coal price (*D_lnCoal*$_t$) and its lags, and the two dummies, Break14 and Break15, indicating the potential "compliance breaks" surrounding the week 26 2014 and week 26 2015. "*BJ*" is short for Beijing ETS, "*CQ*" for Chongqing ETS, "*GD*" for Guangdong ETS, "*HB*" for Hubei ETS, "*SH*" for Shanghai ETS, and "*TJ*" for Tianjin ETS. "*Obs.*" indicates the number of observations. For each equation, the coefficients, standard errors of the coefficients (in parentheses), the R square (*R-squ.*), the F-test statistic (*F-stat.*), the p-value of the F-test (*Prob>F*) are reported. The statistics of three types of post-estimation tests are also reported: Durbin's alternative test for serial correlation, the Breush-Godfrey (BG) serial correlation Lagrange Multiplier (LM) test, the joint F-test statistic (*F-stat.*). The joint F tests are performed for (1) Break14 and its interaction terms, (2) Break15 and its interaction terms, (3) D_$lnBrent_t$ and its lags as well as its interaction terms, (4) D_$lnCoal_t$ and its lags as well as its interaction terms. *, ** and *** denote significance at 1%, 5% and 10% levels. The test was performed for full sample period, from the first operation dates of the ETS pilots till 30 June 2016. "*D*" refers to the first difference. "*L*", "*L2*" and "*L3*" denote the number of lags as 1, 2 and 3.

Figure 1 Weekly average carbon price in seven ETS pilots, China (2013-2016)

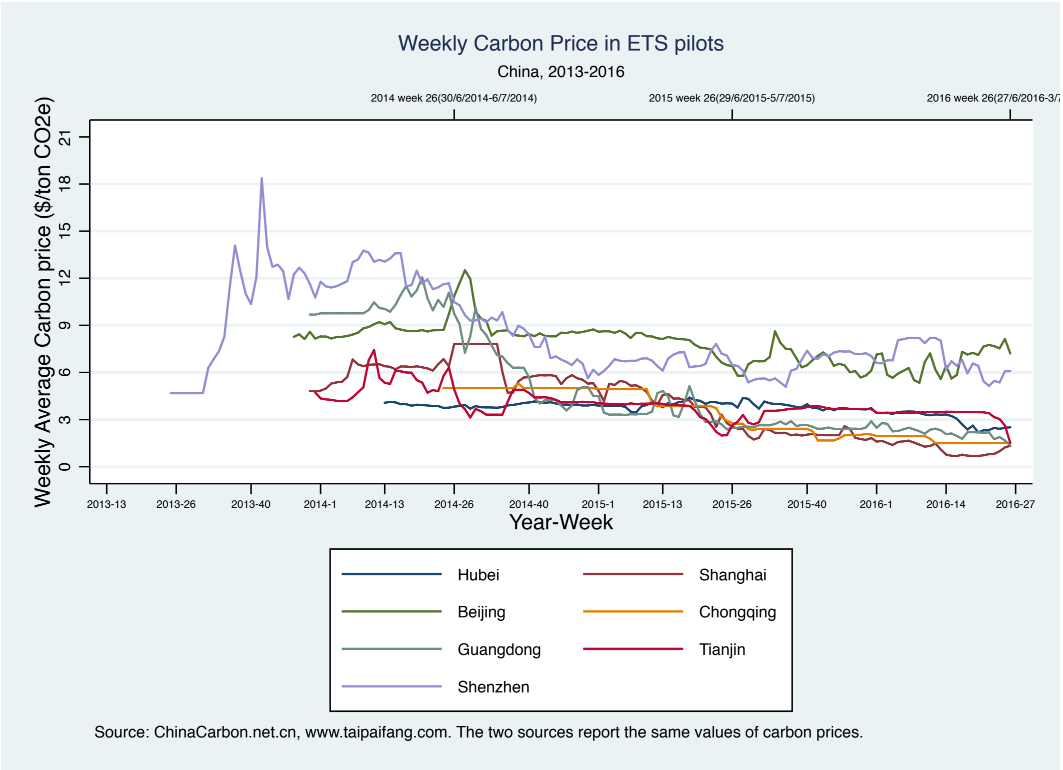
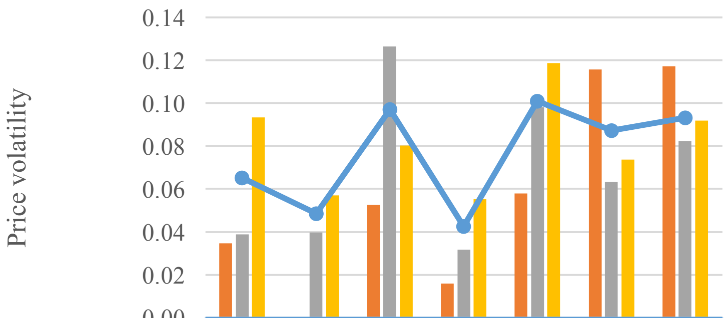


Figure 2 Price volatility in seven ETS pilots



	BJ	CQ	GD	HB	SH	SZ	TJ
1st Year	0.03		0.05	0.02	0.06	0.12	0.12
2nd Year	0.04	0.04	0.13	0.03	0.10	0.06	0.08
3rd Year	0.09	0.06	0.08	0.06	0.12	0.07	0.09
Full sample	0.07	0.05	0.10	0.04	0.10	0.09	0.09

Note: price volatility is estimated by calculating the standard deviation of $\ln Return_t$. Full sample period started from the first operation dates of the ETS pilots till 30 June 2016. "1st Year" refers to the first compliance year starting from June 2013 to June 2014. "2nd Year" refers to the second compliance year during July 2014-30 June 2015. "3rd Year" refers to the third compliance year during July 2015-June 2016. "BJ" is short for Beijing ETS, "CQ" for Chongqing ETS, "GD" for Guangdong ETS, "HB" for Hubei ETS, "SH" for Shanghai ETS, and "TJ" for Tianjin ETS.