Assessing the Implementation of Local Emission Trading Schemes in China: Econometric Analysis of Market Data

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Abstract

Emission trading scheme (ETS) has been used for reducing emissions of industries in developed countries since the 1990s. This study contributes to existing research by focusing on the implementation of local ETSs for reducing carbon dioxide (CO_2) emissions in the context of China. Based on time-series analysis techniques, the study investigates into the market dynamics of the local ETSs in China from their launching dates to 30 June 2017, addressing the relations between energy prices and the prices of China's CO_2 emission allowance (CEA). The price values of CEA and the level of trading volumes vary across the ETS pilots due to their differences in policy features, local business environment and governments' support. Between the two provincial ETSs, Hubei ETS had less volatile price and larger weekly trading volume, while Guangdong ETS had higher CEA price on average. Among the five city ETSs, Tianjin and Chongqing ETSs were not so market-oriented considering their lower prices and much less active trading activities. The regression analyses found that the links between energy prices and CEA prices were different among local ETSs as well, which may be because of different demand and supply dynamics in the ETS markets and energy markets. There was no Granger causality from energy prices to CEA prices in Guangdong or Hubei. With respect to the city ETSs, the steam coal price granger caused the CEA price in Shanghai, and the changes in coal price had a negative short-term effect on the changes in CEA price, indicating that an increase in coal price could arrest coal associated pollution due to a substitution of coal with less carbon-intensive fuels (e.g. natural gas). In Beijing, the results show that the international oil price granger caused the CEA price, and there was a positive effect of the oil price changes on the CEA price changes in the short-run, implying a

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substitution of oil with coal when oil price increases. In addition, the Shanghai Shenzhen 300 stock index granger caused the CEA price in Beijing, Shanghai and Shenzhen, suggesting that the CEA price was affected by the macroeconomic environment. Furthermore, the results suggest that in all local ETSs, the CEA prices were at a higher level at the initial stage but significantly dropped after the compliance deadline in the next calendar year due to decreases in CEA demand. As ETS will continue to be an important tool for climate change mitigation in China, the diverse policy features and performance of the local ETSs served as crucial references for the ETS at national level. The policy implication is that the national ETS should reduce the CEA price volatility caused by energy price fluctuations and put emphasis on local contingencies.

Keywords: Emission trading scheme; local pilots; emission allowance price; energy price

Evaluación de la implementación de esquemas de comercio de emisiones locales en China: análisis econométrico de datos de mercado

Resumen

El esquema de comercio de emisiones (ETS) se ha utilizado para reducir las emisiones de las industrias en los países desarrollados desde los años noventa. Este estudio contribuye a la investigación existente al centrarse en la implementación de ETS locales para reducir las emisiones de dióxido de carbono (CO_2) en el contexto de China. Con base en las técnicas de análisis de series temporales, el estudio investiga la dinámica del mercado de los ETS locales en China desde su fecha de lanzamiento hasta el 30 de junio de 2017, abordando las relaciones entre los precios de la energía y los precios de la emisión de CO_2 en China (CEA). Los valores de los precios de CEA y el nivel de los volúmenes de negociación varían en los programas piloto de ETS debido a sus diferencias en las características de las políticas, el entorno empresarial local y el apoyo de los gobiernos. Entre los dos ETS provinciales, el ETS de Hubei tuvo un precio menos volátil y un mayor volumen de transacciones sema-

nales, mientras que el ETS de Guangdong tuvo un precio de CEA más alto en promedio. Entre los cinco ETS de la ciudad, los ETS de Tianjin y Chongqing no estaban tan orientados hacia el mercado teniendo en cuenta sus precios más bajos y actividades comerciales mucho menos activas. Los análisis de regresión encontraron que los vínculos entre los precios de la energía y los precios del CEA también eran diferentes entre los ETS locales, lo que puede deberse a las diferentes dinámicas de oferta y demanda en los mercados de ETS y los mercados de energía. No hubo causalidad de Granger por los precios de la energía a los precios del CEA en Guangdong o Hubei. Con respecto a los ETS de la ciudad, el precio del carbón a vapor causó el precio del CEA en Shanghai, y los cambios en el precio del carbón tuvieron un efecto negativo a corto plazo en los cambios en el precio del CEA, lo que indica que un aumento en el precio del carbón podría detener la contaminación debida a la sustitución del carbón por combustibles menos intensivos en carbono (por ejemplo, carbón, gas natural). En Beijing, los resultados muestran que el aumento en el precio del petróleo internacional causó el precio del CEA, y hubo un efecto positivo de los cambios del precio del petróleo en los cambios del precio del CEA en el corto plazo, lo que implica una sustitución del petróleo con el carbón cuando el precio del petróleo aumenta. Además, el índice de acciones de Shanghai Shenzhen 300 tuvo un efecto granger sobre el precio del CEA en Beijing, Shanghai y Shenzhen, lo que sugiere que el precio del CEA se vio afectado por el entorno macroeconómico. Además, los coeficientes en los break dummy sugieren que en todos los ETS locales, el precio del CEA se ubicó en un nivel más alto al principio, pero se redujo significativamente en el próximo año debido a la disminución de la demanda del CEA. Dado que el ETS seguirá siendo una herramienta importante para la mitigación del cambio climático en China, las diversas características de las políticas y el desempeño de los ETS locales sirvieron como referencias cruciales para el ETS a nivel nacional. La implicación de la política es que el ETS nacional debería reducir la volatilidad de los precios del CEA causada por las fluctuaciones de los precios de la energía y poner énfasis en las contingencias locales.

Palabras clave: esquema de comercio de emisiones; pilotos locales; precio de permiso de emisión; precio de la energía

评价中国地方排放交易机制的实施：市场数据的计量分析

摘要

20世纪90年代以来，排放交易机制(ETS)一直用于减少发达国家的工业污染物排放。本文通过聚焦中国为减少二氧化碳(CO_2)实施的ETS试点，从而对现有ETS研究作出贡献。本文运用时间序列分析方法研究中国ETS试点自推出之日起至2017年6月30日的市场动态，重点分析了能源价格与中国二氧化碳排放限额(CEA)价格之间的关系。CEA的价格和交易量水平因ETS试点在政策设计、当地经济环境和政府支持力度等方面的差异而有所不同。在两个省级ETS试点中，湖北ETS试点价格波动较小，平均每周交易量较高，而广东ETS试点平均CEA价格较高。在五个城市级的ETS试点中，天津和重庆的ETS试点并不以市场为导向，其价格较低，交易活动也少得多。分析结果表明，能源价格与CEA价格之间的关系在不同ETS试点中也存在差异，这可能是由于其ETS市场和能源市场的需求和供应动态不同。广东和湖北的ETS试点中，能源价格与CEA价格之间没有表现出显著的格兰杰因果关系。至于五个城市ETS试点中，上海的动力煤价格变化是推动CEA价格变化的格兰杰原因，这种影响是负的且是短期的，暗示着煤价的上升将会导致煤炭被低碳燃料（如天然气）代替，从而抑制煤炭燃烧相关的污染。北京的研究结果表明，国际油价变化是引起CEA价格变化的格兰杰原因，这种影响是正的且是短期的，表明油价的上升将会导致石油与煤炭之间的能源替代。此外，沪深300指数变化是引起北京、上海和深圳的CEA价格变化的格兰杰原因，表明CEA价格受到宏观经济环境的影响。此外，结果表明，所有试点的CEA价格在政策实施初始阶段处于较高的水平，但由于CEA需求减少，CEA价格在第二年履约期后均显著下降。ETS将继续作为中国缓解气候变化的重要工具，因而ETS试点的不同政策特点和市场表现将为ETS在全国范围内的实施提供重要参考。且ETS在全国范围内实施时，应当注意能源价格波动引起的CEA价格波动，并重视地区差异性。

关键词：排放交易机制；地区试点；排放许可价格；能源价格

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 of NEPIs in developing countries with limited monitoring and enforcement resources.

More and more scientific evidence shows that greenhouse gas (GHG) emissions contribute to the global climate change, and emission trading scheme (ETS) is an important policy instrument for reducing GHG emissions that the Kyoto Protocol suggested. ETS has been used for emission abatement at the international level such as the European Union (EU) ETS, at the country level such as the South Korea ETS, and at the regional level such as the Regional Greenhouse Gas Initiative. Between 2013 and 2014, seven domestic pilots of ETS were established in China, including two provincial level ETSs and five city level ETSs. Since the end of 2017, China has started to establish the national ETS. Experiences from the pilots become important references for the national ETS.

Following the polluter-pay principle, ETS creates a market for carbon dioxide (CO_2) emission allowances to encourage the internalization of emission abatement costs. If the market functions well, the emission allowance price can reflect the marginal cost of emission abatement and encourage enterprises to adopt low-carbon technologies. One of the major implementation concerns is that targeting enterprises fail to respond in ways anticipated by policymakers due to low economic incentives (Weaver 2010). In practice, the emission allowance price tends to be low and volatile, hardly reflecting the real abatement cost. 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 would have little incentives to adopt costly environmental measures to reduce CO_2 emissions internally.

China is the largest emitter of CO_2 emissions, mainly caused by its enormous size of population and economy, and the high share of coal (more than 60%) in its energy mix (Olivier et al. 2015). Although China has no compulsory GHG reduction obligation in the Kyoto Protocol, it has committed to achieving intensity-based targets partly in response to increasing international pressures that proceeded the Copenhagen negotiation. As its INDC for the Paris Agreement, China promised to reduce its CO_2 emission intensity by 60%–65% by 2030 in relative to 2005 (NDRC of China 2015). To achieve the national CO_2 emission reduction target, China has used many policy instruments and ETS is one of the most important ones.

The first piloting ETS for CO_2 emission reduction in China is Shenzhen ETS, established in June 2013. Subsequently, Shanghai, Beijing, Guangdong, and Tianjin developed ETS pilots by the end of 2013. After that, Hubei and Chongqing developed ETS pilots in 2014. While some similarities of the policy design exist among pilots, such as the use of intensity-based cap, the inclusion of power generation sector, and the use of free allocation, there are variations regarding the policy design across pilots, such as the difference in non-compliance penalties, the difference in sectoral coverage, and the difference in the use of auction to complement free allowance allocation (see Table 1).

All seven ETS pilots in China assign intensity-based caps to participants compared to the use of absolute caps in other ETSs. One of the critical justifications for the intensity-based cap is the uncertainty of the business-as-usual output (Quirion 2005). China's GHG emissions have not reached its peak yet, and the country still keeps a rapid economic development. Under the circumstances, reaching an absolute emission cap can be costly, but setting intensity-based caps ensures flexibility considering the emissions from future

Table 1. Policy Features of ETS Pilots in China

Program (duration)	ETS pilots (2013–present)
Scope	City-level ETS: BJ, SH, SZ, TJ, CQ Provincial-level ETS: HB, GD
Identifying potential participants	Enterprises are capped if they meet thresholds as follows. (1) BJ: annual emission >10,000 tons CO_2e on average during 2009–2012 (mandatory); enterprises with annual energy consumption > 2,000 tce can voluntarily participate. (2) SH: emission >20,000 tons CO_2e in 2010 or 2011 for major industrial sectors; the threshold is >10,000 tons CO_2e for non-industrial sectors (3) SZ: industrial enterprises with emission>3,000 tons CO_2e per year, or public buildings with area >10,000m^2. (4) TJ: annual emission>20,000 tons CO_2e in any year since 2009. (5) CQ: annual emission >10,000 tons CO_2e in any year during 2009–2012. (6) GD: industrial enterprises with annual emission >10,000 tons CO_2e on average or any year in 2010–2012; non-industrial enterprises with emission > 5,000 tons CO_2e (7) HB: emission > 150,000 tons CO_2e for major regulated sectors in 2010 or 2011

Cap coverage	(1) BJ: covering power generation sector, cement, heat supply, petrochemical, car manufacturing, and etc.; public buildings, aviation, large restaurants, hotels and banks (2) SH: covering power generation sector, steel, non-ferrous, paper, rubber, chemicals, petrochemical, textile and etc.; airlines, ports, airports, large commercial shops and hotels (3) SZ: covering 26 industrial sectors as well as power generation sector, gas and water supply; 197 public use buildings; participation open to any financial institution. (4) TJ: covering power generation sector, steel & iron, petrochemical, chemicals, civil construction, heat supply, oil and gas mining (5) CQ: covering power generation sector, steel & iron, cement, metal alloy, calcium carbide, caustic soda, electro-plated aluminum (6) HB: covering power generation sector, steel, cement, non-ferrous, paper, chemicals, automobile manufacturing, glass and etc. (7) GD: covering power generation sector, steel, cement, non-ferrous, paper, ceramics, petrochemical, plastics and etc.
Scale	Share of the cap coverage in the total emissions in the city/province: (1) BJ-40%; (2) SH-57%; (3) SZ-38%; (4) TJ-60%; (5) CQ-40%; (6) GD-55%; (7) HB-35%
Setting enterprise-level targets	Intensity-based emission caps are assigned to participating enterprises through either free allocation or auctioning, and the enterprises can buy more emission allowance from the ETS market: (1) Free allocation through grandfathering approach is the prevalent allocation method across pilots; (2) Auctioning has been used as a complementary allocation method in GD, SH and SZ to allocate a small portion of allowances.
Enforcing compliance	(1) Except CQ and TJ, every ETS pilot has monetary penalties for non-compliance. (2) Additionally, SZ, HB and GD have a further penalty, which is deducting the excess emissions from the following complinace period's emission allowance.

Note: Swartz (2013), Perdan and Azapagic (2011), and relevant Chinese policy documents. "BJ" is short for Beijing, "SH" for Shanghai, "SZ" for Shenzhen, "TJ" for Tianjin, "CQ" for Chongqing, "GD" for Guangdong.

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 intensity-based cap allows rapid economic growth to continue, its effectiveness on emission abatement has a higher uncertainty than using the absolute emission cap.

Compared to more mature ETS such as EU ETS, Chinese ETS is still at the trial stage. After more than four-year operation, the problems of the emission trading markets have become apparent, including low liquidity and high volatility, even though some pilots are a little better than others. China's ETSs generally had a poor performance because of the absence of legal binding forces, excessive allowance allocation, market segmentation, and lack of active investments (Tan and Wang 2017a).

The price of emission allowance is often used for analyzing an emission trading market, as it theoretically responds to the market supply and demand. Factors affecting the price of the CO_2 emission allowance that are commonly identified in the literature include energy prices, macroeconomic indicators, extreme temperature events and institutional events. A summary of this group of studies is shown in Table 2. In these studies, the words such as "impact", "influence", "effect" etc. mostly refer to Granger causality in the sense of inter-temporal precedence, rather than causality "in the colloquial sense of an unavoidable logical link" (Keppler and Mansanet-Bataller 2010). The empirical literature concentrates on the analysis of the EU CO_2 emission allowance (EUA) prices, while there are a small number of studies on the ETS in the United States (Hammoudeh, Nguyen, and Sousa, 2014a; Hammoudeh et al. 2015; Kim and Koo 2010). Literature has examined the Granger causality from crude oil price, natural gas price, and coal price to the price of CO_2 emission allowances, using time series techniques such as GARCH, Vector Auto-regression (VAR), Newey–West Ordinary Least Squares (NW-OLS), Autoregressive Distributed Lag (ADL), Vector Error Correction Model (VECM) and quantile regressions. Alberola, Chevallier, and Chèze (2008), Hammoudeh, Nguyen, and Sousa (2014a,b), Hammoudeh et al. (2015), and Keppler and Mansanet-Bataller (2010) also include electricity price in the analysis in addition to energy prices, assuming that changes in electricity price may affect CO_2 emission allowance price due to the resulting changes in the consumption of electricity, a secondary energy source. This may not happen in China since Chinese electricity price is highly regulated and the price changes are not frequent.

According to the substitution effect theory, the increase in oil price (or natural gas price) would contribute to an increase in CO_2 emission allowance price through a fuel substitution from oil (or natural gas) to more carbon-intensive fuels such as coal. For instance, Boersen and Scholtens (2014) found that oil price, as well as natural gas price, were positive drivers of EUA futures price during the second phase of EU ETS. Alberola, Chevallier, and Chèze

Table 2. Review of Empirical Studies on Factors Affecting CO_2 Emission Allowance Price

Literature	ETS/ Dependent Variable	Time Period	Main Factors Examined	Method
Alberola, Chevallier, and Chèze (2008a,b)	EU ETS/EUA spot price	2005.7–2007.4	Crude oil price, natural gas price, coal price, switch price of CO_2 between coal and natural gas, temperature, electricity price, the compliance break, the announcement of stricter allocation	NW OLS, GARCH
Boersen and Scholtens (2014)	EU ETS/EUA futures price	2008.12–2012.12	Crude oil price, natural gas price, coal price, the switch possibility from coal to natural gas	Threshold GARCH
Chevallier (2011)	EU ETS/EUA futures price	2005.1–2010.7	Crude oil price, natural gas price, coal price, aggregated industrial production index	Markov-switching VAR
Hammoudeh, Nguyen, and Sousa (2014a)	EU ETS/EUA spot price	2006.8–2013.11	Crude oil price, natural gas price, coal price, electricity price	Bayesian Structural VAR
Tan and Wang (2017b)	EU ETS/EUA futures price	2005.4–2016.1	Crude oil price, natural gas price, coal price, macroeconomic indicators	Quantile regression
Creti, Jouvet, and Mignon (2012)	EU ETS/EUA futures price	2005.6–2010.12	Crude oil price, stock index, switch price of CO_2 between coal and natural gas	OLS
Keppler and Mansanet-Bataller (2010)	EU ETS/ EUA spot and futures price	2005.1–2007.12 and 2008	Natural gas price, electricity price, coal price, temperature, stock index	OLS
Koch et al. (2014)	EU ETS/EUA futures price	2008.1–2013.10	Natural gas price, coal price, macroeconomic indicators, the number of issued CERs, electricity production from wind/solar, switch price of CO_2 between coal and natural gas	NW-OLS
Kim and Koo (2010)	Chicago/ CCX[a] trading emission allowance volume	2005.1–2008.11	Crude oil price, natural gas price, coal price, temperature, economy crisis dummy	ADL [b]
Hammoudeh et al. (2015)	US ETS/ Proxied by EUA price	2006.8–2013.11	Crude oil price, natural gas price, coal price, electricity price	NADL[c]
Hammoudeh, Nguyen, and Sousa (2014b)	US ETS/ Proxied by EUA price	2006.7–2013.11	Crude oil price, natural gas price, coal price, electricity price	Quantile regressions

[a] Chicago Climate Exchange (CCX); [b] Autoregressive distributed lag (ADL); [c] Nonlinear autoregressive distributed lag model (NADL).

(2008) explored the drivers of EUA spot price in two sub-periods during January 2005–April 2007 (before and after the "compliance break" in 2016), and found that oil price positively affected the EUA price in both sub-periods. However, some other studies reported a negative relationship between oil price and CO_2 emission allowance price when the substitution effect was not significant. Hammoudeh, Nguyen, and Sousa (2014a) found that when CO_2 emission allowance price was at a high level, oil prices had a substantial negative effect on CO_2 emission allowance price. They explained that the result might be (1) because when CO_2 emission allowance price was high, higher oil price might lead to a substantial drop in all energy consumption and the associated emissions, without encouraging the substitution of coal for oil, or (2) because higher oil price might raise all energy prices and encourage the use of cleaner energy resources.

Some studies revealed a negative relation between coal price and the CO_2 emission allowance price, which is consistent with the substitution effect theory. Hammoudeh, Nguyen, and Sousa (2014a) suggested that in the context of US during 2006–2013, coal price had a negative impact on CO_2 emission allowance price, as a rise in coal price could arrest coal-associated pollution. Hammoudeh et al. (2015) further stated that coal price had a negative but asymmetric impact on the CO_2 emission allowance price in the short term. Compared to a price increase, a price decrease of coal had a more significant impact.

Literature has also examined whether the natural gas price affects the price of the CO_2 emission allowance. Alberola, Chevallier, and Chèze (2008) found that the natural gas price positively impacted EUA spot price while the coal price negatively impacted EUA spot price during January 2005–April 2007. Alberola, Chevallier, and Chèze (2008) also included the switch price between natural gas and coal in the analysis, but there seemed to be a multicollinearity problem among coal price, gas price, and the switch price. Tan and Wang (2017b) summarized that during the three phases of EU ETS, the relationships between EUA price and energy prices vary from one phase to another. It is reasonable as the supply and demand curves of energy sources were changing during the three phases. Same could be said about the supply and demand of emission allowances.

Some studies examined the impact of macroeconomic indicators, such as aggregated industrial production, stock index, economy crisis dummy and so on. The macroeconomic indicators can influence CO_2 emission allowance price either through affecting the expectation of economic growth and the future emission allowance demand or through affecting the changes of energy price (Tan and Wang 2017b). However, only a few of the studies showed that the impact of macroeconomic indicators is significant (Chevallier 2011; Koch et al. 2014). Literature also found structural breaks of CO_2 emission allowance price series due to institutional decisions or events. For instance, there was often a compliance break in year

T when the regulated firms actively manage their compliance after the disclosure of verified emission and before the submission deadline of allowances valid for year T-1 (Alberola, Chevallier, and Chèze 2008).

There are limited empirical studies on the price dynamics of the piloting ETSs in China. Among a few recent empirical studies that did focus on CO_2 emission allowance (CEA), Zeng et al. (2017), Zhang and Zhang (2016), and Fan and Todorova (2017) examined the relationships between CEA price and energy prices. Zeng et al. (2017) employed a structural VAR approach showing that during April 2014–November 2015, coal price had a significant and positive impact on Beijing CEA price within a short period, but it became negative after two days when firms started to substitute coal with less carbon-intensive energy sources or use carbon-reduction measures. Based on a quantile regression method, Zhang and Zhang (2016) argued that oil price had a slight positive impact on the Shanghai CEA price, consistent with the substitution effect theory. Fan and Todorova (2017) investigated into the response of emission allowance price to energy prices and macroeconomic indicators in Beijing, Shenzhen, Guangdong and Hubei from the launching dates to December 2016. The results showed that Hubei CEA price was weakly related to natural gas price, while Guangdong CEA price had a significant positive relation with oil price. However, overall, the empirical studies on the influence from energy prices to CEA prices have been scarce and scattered.

Given that there are still few empirical studies on the prices of China's CEA and considering that ETS will continue to play an important role in reducing CO_2 emissions in China, this study aims at examining the price dynamics of CEA, with a focus on the relations between energy markets and ETS markets. The rest of the article is organized as follows. Section 2 details the data and method. Section 3 starts with the descriptive analysis of the CEA price and trading volume data, following by co-integration tests and multivariate regressions to examine the relationship between energy prices and CEA price. Section 4 presents concluding remarks and policy implications of the findings.

2. Data and Method

2.1. Data

We collected the daily CEA price data and daily transaction volume data from the website (www.tanpaifang.com) that compiles the market data published by Emission Exchanges of the seven ETS pilots. The website was created in 2012, organized by the Zhongke Carbon Information Technology Research Institute, providing data, regulatory information and consultancy about ETS. As Chinese ETS allows for only spot trading, all price data collected are closing spot trading price data. The market data of China's seven piloting ETSs can also be found from the website (www.chinacarbon.net.cn) organized by Climate Limited, which is a UN-accredited online media company. Data from the

two sources are identical. This study collected the daily market data of the seven ETS pilots from their launching dates to 30 June 2017, considering that in the second half of year 2017, all ETS pilots were making adaptions since the country was going to establish the national ETS by the end of the year. The currency unit of all price data is changed from RMB to US dollar ($), using the currency conversion rates provided by OECD.

In most local ETSs, the daily CEA data, either price or trading volume, are missing for many days, which impede the ability to do the analysis at the daily frequency. Similar to Fan and Todorova (2017), we used the weekly price data ($Price_t$, \$/ton CO_2e) for analysis. For instance, given any week T, if the daily CEA price data is available for n days (n≤7) of the week, the weekly price data will be calculated by averaging the daily price data: $Price_T = (\sum_1^n \text{Price}_i)/n$. Also, we generated the weekly trading volume data ($Volume_t$, 1000 ton CO_2e/week) by totaling the daily trading volume in the week. Given any week T, if the daily trading volume data is available for n days (n≤7) of the week, the weekly trading volume data will be calculated by $Volume_T = \sum_1^n \text{Volume}_i$. Thus, in week T, we can think it as the $Volume_T$ amount of CEA was traded in the week at the $Price_T$. Further, a time-series variable of price return is generated for each price variable for analysis using the equation $\ln(Price_t/Price_{t-1})$.

On energy markets, we collected data on the oil price, coal price, and natural gas price, in order to address the relations between energy prices and CEA prices. Coal consumption is one of the major sources of CO_2 emission in China, and the consumption of crude oil or natural gas is much less. We expect that the demand for CEA will increase due to substitution effect if the price of less carbon-intensive fuel (e.g. oil) increases, or if the price of more carbon-intensive fuel (e.g. coal) decreases. Given there is no coal price index for each pilot region, the coal price we use is the Bohai Rim 5500 kcal/kg stream coal spot price ($Coal_t$, RMB/ton, weekly), which was also used by Fan and Todorova (2017). It is a most important benchmark domestic coal price index in China. It is 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 and can be collected from the website www.coalchina.org.cn. We collected natural gas price data from CEIC database, which is monthly average spot price data (RMB/ton) of Liquefied Natural Gas (LNG) released by China Petroleum and Chemical Industry Federation. We converted the monthly data to a weekly price variable of LNG (LNG_t, RMB/ton, weekly) by assuming that different weeks during the same month have the same price. The oil price ($Brent_t$, \$/barrel, weekly) is the weekly Europe spot price of Brent crude oil and petroleum products, collected by the website of US Energy Information Administration. Chinese oil import dependence is larger than 60%, so we use the Brent crude oil price to reflect the influence of the international price shocks. $Coal_t$ and

$Brent_t$ are collected from 2013 Week 25 when the first piloting ETS started to operate in Shenzhen. Available observations of LNG_t only started from 1st January 2014. Data are all collected till 30th June 2017. The currency unit is all converted to US dollar ($) using OECD currency conversion rates.

Further, we include the Shanghai Shenzhen 300 stock index data (31st December 2014=1000, daily) to capture the relation between the macroeconomic level and the CEA price. The data was collected from CEIC database for the time period of 2013 Week 25–2017 Week 26 and converted to weekly data ($Stock_t$, weekly) by averaging the daily stock index data. The macroeconomic level can affect the demand and supply of CEA through affecting the production activities and the associated CO_2 emissions. Thus, we expect that CEA prices increase when $Stock_t$ increases.

We also add three dummy variables to test the structural changes of the regressions. They are *Break2014*, *Break2015*, and *Break2016*, respectively taking a value of 1 from 2014 Week 27, 2015 Week 27 and 2016 Week 27. So there are four sub-periods of the dataset, launching dates -June 2014 (1st Period), July 2014–June 2015 (2nd Period), July 2015–June 2016 (3rd Period), and July 2016–June 2017 (4th Period). The compliances of regulated enterprises in any local ETS follow a particular calendar. At the beginning of year T in each ETS pilot, the regulated enterprises receive their CEA allocations for year T. The regulated enterprises have to submit their emission reports to the regulator in March of year T or the end of February of year T, with dates varying over pilots, and then a third party will verify their reports. In April, the regulated enterprises should submit the verified emission

Table 3. Test for Structural Breaks of $\ln Price_t$

ETS	Full Sample Period		AR Lags	Break2014 (2014 Week 26)	Break2015 (2015 Week 26)	Break2016 (2016 Week 26)
	From Launching Date	To		Chi Statistic	Chi Statistic	Chi Statistic
BJ	28-Nov-2013	30-Jun-2017	3	4.275	16.827***	19.453***
CQ	19-Jun-2014	30-Jun-2017	2	—	2.577	2.920
SH	26-Nov-2013	30-Jun-2017	2	2.237	10.251**	8.198**
SZ	18-Jun-2013	30-Jun-2017	3	41.766***	18.991***	5.935
TJ	26-Dec-2013	30-Jun-2017	2	9.561**	2.541	24.578***
GD	16-Dec-2013	30-Jun-2017	3	9.699**	11.305**	3.419
HB	02-Apr-2014	30-Jun-2017	1	0.021	5.311*	5.175*

Note: $lnPrice_t$ refers to the logarithmic form of CEA price. ***, ** and * denote significance at 1%, 5% and 10% levels. "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. "—" denotes the statistics are not available due to the characteristics of the original data.

reports, and at the end of June (around week 26 of the year), they have to submit the allowances valid during year T-1 to comply with their targets of year T-1. So, the trading of emission allowances is relatively active between April and June of year T. We ran an auto-regression (AR) model of logarithmic CEA price data and used a Wald test to see if there is a structural break of the coefficients after the week 26 of each year. The results in Table 3 show that the AR coefficients of $lnPrice_t$ do have structural changes either after 2014 Week 26, or after 2015 Week 26, or after 2016 Week 26, in all ETS pilots except Chongqing. Chongqing ETS has very low-level trading activities and its CEA price might be artificially set at a certain level during weeks when trading volumes were zero, not reflecting the market demand and supply. Thus, it is not surprising that Chongqing CEA price does not exhibit compliance break as other piloting ETSs.

2.2. Methods

This study uses time-series analysis techniques. The Akaike Information Criterion (AIC) is used for choosing the number of lags in all tests. Augmented Dickey-Fuller (ADF) tests are applied to check the unit roots of variables. This study performed three forms of ADF tests: random walk model with drift, random walk model with a trend, and pure simple random walk model. The Philips-Perron (PP) test is performed with and without trend as a robustness check.

To investigate the relationships between energy prices and CEA prices, this study first uses Johansen's test to see if there are long-run equilibrium relations between energy prices and CEA prices. Second, it performed time-series regressions using the technique of multivariate OLS or NW-OLS which works with stationary data series. If there is a significant serial correlation problem, the Newey-West (NW) heteroscedasticity-and-autocorrelation-consistent estimator will be used. If not, the regressions will be estimated with the robust estimator. Three types of post-estimation tests were performed: Durbin's alternative test for serial correlation, the Breush-Godfrey serial correlation Lagrange Multiplier test, and the joint F-test.

Therefore, the role played by Brent crude oil price and coal price on CEA price is estimated using the first specification (Eq.1):

$$\ln\text{Return}_{i,t} = a_{i,0} + a_{i,1}(LD)lnReturn_{i,t} + a_{i,2}(LD)\ln Brent_t + a_{i,3}(LD)lnCoal_t + a_{i,4}Break2014 + a_{i,5}Break2015 + a_{i,6}Break2016 + \mu_{i,t}. \quad (1)$$

The second specification (Eq.2) takes account of stock index:

$$\ln\text{Return}_{i,t} = a_{i,0} + a_{i,1}(LD)lnReturn_{i,t} + a_{i,2}(LD)\ln Brent_t + a_{i,3}(LD)lnCoal_t + a_{i,7}(LD)lnStock_t + a_{i,4}Break2014 + a_{i,5}Break2015 + a_{i,6}Break2016 + \mu_{i,t}. \quad (2)$$

The third specification (Eq.3) adds the price data of LNG, which is only available since 2014 week 1.

$$\ln\text{Return}_{i,t} = a_{i,0} + a_{i,1}(LD)lnReturn_{i,t} + a_{i,2}(LD)\ln Brent_t + a_{i,3}(LD)lnCoal_t + a_{i,7}(LD)lnLNG_t + a_{i,8}(LD)lnStock_t + a_{i,4}Break2014 + a_{i,5}Break2015 + a_{i,6}Break2016 + \mu_{i,t}. \quad (3)$$

In the equation, $lnReturn_{i,t}$ is the price return of CEA at period t in the ETS pilot i. Price return series are used because they are all stationary. L denotes the lag operator. D denotes the first difference. $\mu_{i,t}$ is the error term. Eq.3 is the main equation we want to estimate, while Eq.1 and Eq.2 are the restricted equations. The equations are adjusted from ADL model. Coefficients on lagged log differences of a variable reflect the short-run effects, while the joint F-test on all values of a variable tells the Granger causality.

3. Empirical Analysis

3.1. Descriptive Analysis

Table 4 displays the descriptive statistics of CEA price, price returns and trading volumes. Beijing and Shenzhen ETSs had the highest CEA prices on average, which were 7.805 and 6.911 \$/ton CO_2e respectively. Shenzhen CEA price is highly skewed, with a large right-handed tail, meaning that the majority of the price data is lower than the average price. The distribution of Beijing CEA price, on the other hand, is both positively skewed and leptokurtic. The largest CEA price happened at Shenzhen which was 18.360 \$/ton CO_2e in week 42 of 2013. Chongqing ETS had the lowest average CEA price, 3.32 \$/ton CO_2e. Based on a two-region dynamic CGE model, Wang et al. (2015) suggested that the carbon price should be about 38\$ CO_2e for reaching the Copenhagen target of 40%–50% reduction of CO_2 emission intensity toward 2020 in relative to 2005 level. However, even in Shenzhen, its highest carbon price was less than 20\$/ton CO_2e, far from the ideal price suggested by Wang et al. (2015). For Chongqing ETS, its price once decreased to 0.163 \$/ton CO_2e, which provided very poor incentives for emitters to make environmental changes.

In most piloting ETSs, CEA prices were at a high level in the initial operation stage and exhibited a general decrease trend over time, which may explain the positive skewness in most cases (see Table 4). 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 CEA price gradually decreased to about 5 \$/ton CO_2e by the end of 2014. From January 2015 to June 2017, the CEA price reached a relatively stable status, ranging between 3 and 8 \$/tonCO_2e. Hubei CEA prices decreased from about 4 \$/ton CO_2e in 2014 to less than 3\$/ton CO_2e in 2017, but the distribution showed a slight negative skewness. Chongqing CEA price, however, had a peak in the end of 2016 due to stricter CEA allocation, but it decreased to less than 1\$/ton CO_2e in the second quarter of 2017.

We can see the descriptive statistics of the spot trading volumes from Table 4 and Figure 1. $Volume_t$ denotes the total trading volume of CEA in each week. It was quite different across ETS pilots, ranging from 16422 tons CO_2e/week in Chongqing ETS to 242541 tons CO_2e/week in Guangdong ETS. The two provincial level ETSs, Guangdong, and Hubei, obviously have the higher amount of weekly trading volumes than the five city-level ETSs. But, the maximum trading volume happened

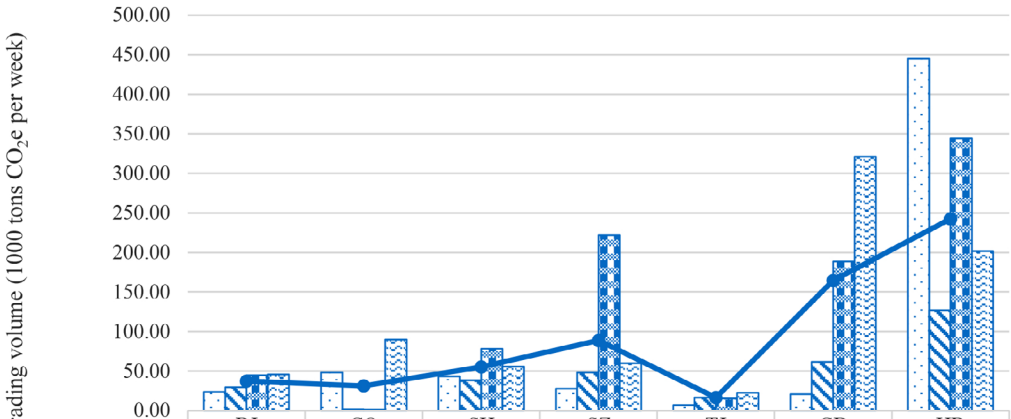
Table 4. Descriptive Statistics of CEA Price, Price Returns and Trading Volumes

Market		City Level ETS					Provincial Level ETS	
		BJ	CQ	SH	SZ	TJ	GD	HB
$Price_t$ (\$/ton CO_2e)	Obs.	187	159	184	210	183	184	170
	Mean	7.805	3.133	3.894	6.911	3.424	4.150	3.326
	Std. Dev.	1.091	1.726	2.114	3.048	1.156	3.019	0.718
	Min.	5.343	0.163	0.676	3.102	1.054	1.295	1.582
	Max.	12.507	7.152	7.814	18.360	7.421	12.053	4.399
	Skewness	0.587	0.131	0.032	1.199	0.468	1.279	−0.457
	Kurtosis	5.786	1.793	1.640	3.404	3.355	3.091	1.666
$lnReturn_t$	Obs.	186	158	183	209	182	183	169
	Mean	0.000	−0.020	0.001	0.000	−0.006	−0.008	−0.004
	Std. Dev.	0.060	0.198	0.095	0.113	0.100	0.098	0.051
	Min.	−0.210	−0.931	−0.355	−0.346	−0.544	−0.314	−0.259
	Max.	0.225	0.814	0.320	0.530	0.547	0.303	0.225
	Skewness	0.363	−0.424	0.024	0.585	0.018	−0.004	−0.701
	Kurtosis	6.447	11.558	6.398	6.169	13.522	4.462	10.513
$Volume_t$ (1000 ton CO_2e per week)	Obs.	187	159	184	210	183	184	170
	Mean	37.238	31.296	55.309	88.875	16.422	164.625	242.541
	Std. Dev.	84.351	185.844	137.582	380.085	105.425	336.122	380.081
	Min.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	25th percentile	0.620	0.000	0.053	3.640	0.000	0.770	64.343
	Median	5.000	0.000	12.447	16.904	0.360	23.540	133.683
	75th percentile	25.523	0.144	48.594	68.291	1.380	174.190	258.081
	Max.	565.091	2166.620	1113.833	4010.471	1083.470	2449.509	3217.207
	Skewness	3.489	9.954	4.797	9.408	8.280	3.630	4.773
	Kurtosis	16.516	111.895	29.626	93.829	74.976	19.120	31.790
	Number of zero observations	3	111	43	9	60	19	2

Note: "*Std. Dev.*" indicates standard deviation; "*Obs*" indicates the number of observations. "*Min*" and "*Max*" are short for minimum and maximum respectively. $Price_t$ refers to a time-series variable of weekly CEA prices. $Volume_t$ refers to a time-series variable of weekly CEA trading volume. $lnReturn_t$ refers to the logarithmic form of CEA price returns. $lnReturn_t = \ln(Price_t/Price_{t-1})$.

at Shenzhen ETS, when 4 million tons CO_2e were traded in 2016 week 12. Among the city-level ETSs, Shenzhen has the largest weekly trading volume on average, followed by Shanghai and Beijing. In Chongqing and Tianjin, however, there are respectively 111 weeks and 60 weeks when zero transactions were made on the ETS markets, implying very low-level participation of

the regulated enterprises. It may reflect deeper problems of the two ETSs: loose enforcement and over-supply of CEA.



	BJ	CQ	SH	SZ	TJ	GD	HB
1st Period	23.50	48.33	43.40	27.90	6.83	20.89	444.86
2nd Period	29.71	1.74	38.36	48.35	16.37	61.61	127.00
3rd Period	44.56	1.20	78.32	221.71	15.54	188.47	344.57
4th Period	45.63	89.97	55.66	59.89	22.34	321.20	201.58
Full sample	37.24	31.30	55.31	88.87	16.42	164.63	242.54

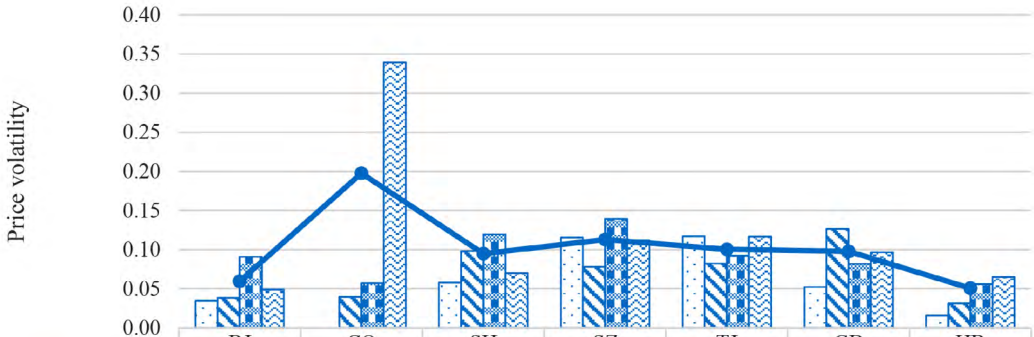
Note: Full sample period started from the first operation dates of the ETS pilots till 30 June 2017.

Figure 1. Average Weekly Trading Volume of CEA in Seven ETS Pilots

In each ETS, the trading activities are more frequent and involve larger trading volumes toward the compliance deadline. In most time of the year, the trading activities are relatively sporadic and with smaller trading volumes. Thus, the trading volume variables all exhibit the asymmetric and leptokurtic distribution, with high-level positive skewness and pronounced excess kurtosis.

The standard deviation of CEA price returns ($lnReturn_t$) can be considered as a measure of price volatility. We use it to compare the market risks between local ETSs. Figure 2 shows the price volatility over different time periods, launching dates -June 2014 (1st Period), July 2014–June 2015 (2nd Period), July 2015–June 2016 (3rd Period), and July 2016–June 2017 (4th Period). We can see that each ETS pilot exhibits a variation of price volatility in different sub-periods. Although Hubei ETS had low CEA price on average, its price volatility was the lowest compared to other piloting ETSs, but it became more and more volatile over time. Beijing ETS had a relatively low volatility but experienced a higher level of volatility during July 2015–June 2016. Chongqing CEA price had the highest volatility, and it was the most volatile during July 2016–June 2017.

We can see that different local ETSs perform so differently that the operation of the national ETS can be expected to be more challenging. Overall, Beijing and Shenzhen ETSs seem



	BJ	CQ	SH	SZ	TJ	GD	HB
1st Period	0.03		0.06	0.12	0.12	0.05	0.02
2nd Period	0.04	0.04	0.10	0.08	0.08	0.13	0.03
3rd Period	0.09	0.06	0.12	0.14	0.09	0.08	0.06
4th Period	0.05	0.34	0.07	0.11	0.12	0.10	0.06
Full sample	0.06	0.20	0.09	0.11	0.10	0.10	0.05

Note: price volatility is estimated by the standard deviation of price returns.

Figure 2. Price Volatility of CEA in Seven ETS Pilots

to operate better than other city-level ETSs, with their high-level CEA prices and active trading activities. Regarding provincial level ETS, Guangdong has higher CEA price, while Hubei has lower volatility and larger weekly trading volume. Chongqing and Tianjin ETSs are not so successful considering their low CEA prices and scarce trading transactions. Therefore, we do not include Chongqing and Tianjin in the regression analysis, as their CEA prices may be artificially set in the weeks with zero transactions, not really relating to the market demand and supply.

Table 5 contains the descriptive statistics of crude oil price, coal price and Shanghai Shenzhen 300 stock index during 2013 week 25–2017 week 26, and LNG price data during 2014 week 1–2017 week 26. Shanghai Shenzhen 300 stock index has the largest volatility because of the nature of the stock index data.

3.2. Unit Root Tests and Johansen's Tests

We took logarithmic forms of all price variables and tested their unit roots. Table 6 displays the results. Not all of the logarithmic forms of the variables is integrated of order zero, meaning that the logarithmic forms of some variables are not stationary. The logarithmic differences of all CEA price variables (i.e. price returns) are stationary, and the logarithmic differences of energy prices and the stock index are also stationary. Thus, we use logarithmic differences of the price variables throughout the following regression analysis.

We applied Johansen's tests for *I(1)* logarithmic price variables that are integrated of order one, including Chongqing CEA price, Hubei CEA price, Shanghai CEA price, Brent oil price and LNG price. We used the tests for every two *I(1)* logarithmic variables

in order to see whether they have long-run equilibrium relationships. However, we can see from Table 7 that there is no significant long-run equilibrium relationships between the variables.

Table 5. Descriptive Statistics of Energy Prices and Stock Index

Var.		Coal Price ($Coal_t$)	Brent Oil Price ($Brent_t$)	LNG Price (LNG_t)	Shanghai Shenzhen 300 Stock Index ($Stock_t$)
Full sample	From	2013 Week 25	2013 Week 25	2014 Week 1	2013 Week 25
	To	2017 Week 26	2017 Week 26	2017 Week 26	2017 Week 26
Unit		$/ton	$/barrel	$/ton	Dimensionless
Obs.		210	210	182	210
Mean		78.123	69.378	586.724	3096.085
Std. Dev.		12.421	28.166	129.759	704.039
Min.		55.840	27.760	428.959	2116.750
Max.		101.840	116.030	804.167	5324.406
Skewness		−0.380	0.493	0.215	0.508
Kurtosis		1.791	1.550	1.474	3.111

Table 6. Test for Unit Roots

Price Returns	Stationary?	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)	
BJ: CEA	Yes	183	−9.249***	−14.191***	−9.224***	−14.151***	−9.249***	I(0)
CQ: CEA	Yes	154	−7.366***	−7.660***	−7.421***	−7.677***	−7.366***	I(1)
GD: CEA	Yes	179	−9.554***	−12.210***	−9.616***	−12.218***	−9.554***	I(0)
HB: CEA	Yes	165	−10.173***	−13.940***	−10.174***	−13.928***	−10.173***	I(1)
SH: CEA	Yes	179	−4.577***	−10.568***	−4.680***	−10.604***	−4.577***	I(1)
SZ: CEA	Yes	205	−9.581***	−19.583***	−9.667***	−19.647***	−9.581***	I(0)
TJ: CEA	Yes	178	−8.455***	−9.646***	−8.444***	−9.632***	−8.455***	I(0)
Coal	Yes	205	−4.610***	−7.406***	−4.729***	−7.625***	−4.610***	I(0)
Brent Oil	Yes	205	−7.433***	−10.641***	−7.436***	−10.621***	−7.433***	I(1)
LNG	Yes	177	−5.450***	−13.144***	−5.432***	−13.120***	−5.450***	I(1)
shsz300	Yes	205	−5.682***	−11.200***	−5.670***	−11.184***	−5.682***	I(0)

Note: "Z(t)" refers to the statistic of ADF or PP unit root test. ***, ** and * denote significance at 1%, 5% and 10% levels. "Integ. Order" refers to order of integration.

3.3. Multivariate Regressions for Provincial ETSs

Table 8 displays the regression results for the two provincial level ETSs, Guangdong ETS and Hubei ETS. The dependent variables are the CEA price returns ($lnReturn_t$) of Guangdong and Hubei respectively, while the independent variables are the logarithmic dif-

Table 7. Johansen's Test for Co-Integration Ranks

Hypotheses		H0: Rank=0 H1: Rank=1	H0: Rank=1 H1: Rank=2
Logarithmic price variables	CQ CEA & Brent Oil	6.687	1.255
	HB CEA & Brent Oil	4.380	1.176
	SH CEA & Brent Oil	8.859	1.715
	CQ CEA & LNG	4.849	0.134
	HB CEA & LNG	9.642	1.017
	SH CEA & LNG	3.351	1.491
5% critical value		15.410	3.760

Note: ** denote significance at 5% level. Logarithmic prices were used for the Johansen's co-integration tests.

Table 8. Multivariate Regressions for Provincial Level ETSs

	Guangdong ETS			Hubei ETS		
	Eq.1	Eq.2	Eq.3	Eq.1	Eq.2	Eq.3
L1. $\ln Return_t$	0.089	0.082	0.090	−0.101	−0.102	−0.101
	(0.080)	(0.079)	(0.082)	(0.207)	(0.210)	(0.212)
L2.$\ln Return_t$	−0.265***	−0.269***	−0.267***	−0.106	−0.098	−0.096
	(0.080)	(0.081)	(0.081)	(0.137)	(0.139)	(0.141)
L1D.$\ln Brent_t$	0.101	0.096	0.120	0.068	0.078	0.084
	(0.158)	(0.154)	(0.160)	(0.095)	(0.101)	(0.092)
L2D.$\ln Brent_t$	−0.058	−0.061	−0.067	−0.074	−0.075	−0.071
	(0.164)	(0.165)	(0.166)	(0.081)	(0.082)	(0.084)
L1D.$\ln Coal_t$	−1.433*	−1.433*	−1.545*	0.313	0.311	0.343
	(0.786)	(0.810)	(0.838)	(0.337)	(0.348)	(0.348)
L2D.$\ln Coal_t$	0.925	0.864	0.939	−0.116	−0.112	−0.143
	(0.584)	(0.588)	(0.613)	(0.351)	(0.353)	(0.348)
L1D.$\ln LNG_t$			0.548			−0.111
			(0.487)			(0.199)
L2D.$\ln LNG_t$			−0.031			0.161
			(0.302)			(0.246)
L1D.$\ln Stock_t$		0.181	0.135		0.050	0.061
		(0.253)	(0.244)		(0.110)	(0.116)
L2D.$\ln Stock_t$		0.082	0.092		−0.220	−0.234
		(0.199)	(0.203)		(0.148)	(0.146)
Break2014	−0.029	−0.034*	−0.033	0.010	0.012	0.012
	(0.020)	(0.019)	(0.020)	(0.008)	(0.009)	(0.008)

Break2015	0.018	0.025	0.026	−0.013	−0.017*	−0.017*
	(0.019)	(0.018)	(0.018)	(0.009)	(0.009)	(0.009)
Break2016	0.026	0.023	0.020	0.005	0.007	0.007
	(0.019)	(0.019)	(0.019)	(0.012)	(0.012)	(0.012)
Constant	−0.003	−0.002	−0.001	−0.008	−0.007	−0.007
	(0.013)	(0.013)	(0.015)	(0.005)	(0.005)	(0.006)
Obs.	181	181	179	167	167	167
R-squ.	0.117	0.121	0.132	0.034	0.050	0.055
F-stat.	2.150	1.900	1.660	0.510	0.640	0.870
Prob>F	0.028	0.043	0.074	0.863	0.796	0.588
Durbin's alternative test	2.190	1.954	1.676	0.001	0.285	0.523
BG LM test	2.302	2.081	1.811	0.001	0.309	0.572
Procedure	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust
Joint F-stat for $D.lnBrent_t$	0.240	0.240	0.330	0.540	0.580	0.630
Joint F-stat for $D.lnCoal_t$	2.040	1.850	1.940	0.470	0.440	0.510
Joint F-stat for $D.lnLNG_t$			0.650			0.400
Joint F-stat for $D.lnStock_t$		0.370	0.300		1.140	1.350

Note: The dependent variable is the price returns ($lnReturn_t$) of CEA in the ETS. Durbin's alternative test and Breusch–Godfrey (BG) LM test are the tests for autocorrelation. "*Joint F-stat*" refers to the F statistic of the joint significance test on the lags of log differences of energy variables and the stock index variable. ***, ** and * denote significance at 1%, 5% and 10% levels. Standard errors are in parentheses.

ferences of energy prices and the stock index as well as the structural break dummies. The regressions are all estimated using the robust estimator rather than Newey-West estimator as there is no significant serial correlation problem. The last four rows of Table 8 show the results of the joint F-tests, which test the joint significance of coefficients on all lag values of a variable.

We can see that the one week lagged coal price return ($D.lnCoal_t$) had a significantly negative effect on Guangdong CEA price returns. It means that the increase of coal price led to the decrease of Guangdong CEA price in short term, which is consistent with the theory that when coal price is high, the industrial enterprises substitute coal with less carbon-intensive fuels, reducing CEA demand. But, the short-term effect became insignificant after two weeks. The joint F-test indicates that the changes in coal price do not significant-

Table 9. Multivariate Regressions for City Level ETSs

	Beijing ETS			Shanghai ETS			Shenzhen ETS		
	Eq.1	Eq.2	Eq.3	Eq.1	Eq.2	Eq.3	Eq.1	Eq.2	Eq.3
L1. $\ln Return_t$	−0.060	−0.060	−0.055	0.220*	0.224*	0.227*	−0.354***	−0.367***	−0.544***
	(0.082)	(0.083)	(0.084)	(0.127)	(0.132)	(0.130)	(0.086)	(0.087)	(0.069)
L2.$\ln Return_t$	−0.217**	−0.194*	−0.207**	−0.145	−0.145	−0.128	−0.176**	−0.192***	−0.260***
	(0.099)	(0.104)	(0.104)	(0.098)	(0.100)	(0.095)	(0.068)	(0.069)	(0.072)
L1D.$\ln Brent_t$	0.268**	0.253**	0.283**	0.073	0.070	0.064	0.129	0.104	0.009
	(0.116)	(0.113)	(0.119)	(0.171)	(0.173)	(0.180)	(0.270)	(0.249)	(0.256)
L2D.$\ln Brent_t$	−0.189	−0.194	−0.196	−0.058	−0.055	−0.076	−0.100	−0.110	−0.133
	(0.122)	(0.118)	(0.120)	(0.171)	(0.171)	(0.166)	(0.216)	(0.213)	(0.198)
L1D.$\ln Coal_t$	−0.162	−0.173	−0.187	−0.872**	−0.876**	−0.967**	−0.531	−0.564	−0.428
	(0.269)	(0.257)	(0.282)	(0.424)	(0.425)	(0.451)	(0.500)	(0.482)	(0.559)
L2D.$\ln Coal_t$	0.554	0.523	0.546	0.290	0.315	0.390	−0.780	−0.863	−0.635
	(0.405)	(0.356)	(0.388)	(0.542)	(0.546)	(0.558)	(0.687)	(0.709)	(0.830)
L1D.$\ln LNG_t$			0.097			0.748**			−0.200
			(0.192)			(0.379)			(0.386)
L2D.$\ln LNG_t$			0.295			−0.649			0.083
			(0.189)			(0.450)			(0.416)
L1D.$\ln Stock_t$		0.080	0.070		−0.104	−0.180		0.207	0.054
		(0.150)	(0.159)		(0.256)	(0.267)		(0.251)	(0.279)
L2D.$\ln Stock_t$		0.271*	0.235		0.037	0.106		0.499*	0.590**
		(0.160)	(0.162)		(0.272)	(0.287)		(0.267)	(0.269)
Break2014	−0.021**	−0.028***	−0.029***	−0.037**	−0.036*	−0.035*	−0.048**	−0.062***	−0.032*
	(0.010)	(0.010)	(0.010)	(0.018)	(0.019)	(0.020)	(0.020)	(0.021)	(0.017)
Break2015	0.013	0.022	0.022	0.009	0.007	0.008	0.023	0.041*	0.042**
	(0.013)	(0.014)	(0.013)	(0.022)	(0.024)	(0.024)	(0.020)	(0.021)	(0.021)
Break2016	−0.006	−0.010	−0.012	0.043**	0.043*	0.042*	0.006	−0.001	−0.004
	(0.014)	(0.014)	(0.015)	(0.021)	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)
Constant	0.012	0.013*	0.017**	0.015	0.015	0.014	0.022	0.023	−0.009
	(0.007)	(0.007)	(0.008)	(0.012)	(0.013)	(0.014)	(0.017)	(0.017)	(0.013)
Obs.	184	184	179	181	181	179	207	207	179
R-squ.	0.128	0.150	0.163	0.113	0.114	0.145	0.137	0.159	0.270

F-stat.	1.680	1.860	1.780	1.810	1.510	1.680	3.400	3.110	5.700
Prob>F	0.098	0.048	0.049	0.069	0.131	0.070	0.001	0.001	0.000
Durbin's alternative test	0.736	0.769	0.888	0.257	0.126	0.137	1.083	0.021	0.371
BG LM test	0.780	0.824	0.964	0.273	0.136	0.149	1.138	0.022	0.404
Procedure	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust	OLS, robust
Joint F-stat for $D.lnBrent_t$	3.140**	3.150**	3.460**	0.180	0.100	0.130	0.140	0.150	0.310
Joint F-stat for $D.lnCoal_t$	0.950	1.080	0.990	2.340	2.300	2.480*	2.390*	2.830*	1.150
Joint F-stat for $D.lnLNG_t$			1.260			0.230			0.180
Joint F-stat for $D.lnStock_t$		2.720*	1.930		0.090	2.800*		2.030	2.410*

Note: The dependent variable is the price returns ($lnReturn_t$) of CEA in the ETS. *, ** and *** denote significance at 1%, 5% and 10% levels. Standard errors are in parentheses.

ly granger cause the changes in CEA price of Guangdong. In Hubei, however, we found no significant short-term effects or Granger causality between energy prices and CEA prices.

The results also show that there was a slight decrease of Guangdong CEA price after June 2014 and a slight decrease of Hubei CEA price after June 2015. Guangdong ETS started to operate from the end of 2013, whereas Hubei ETS was established in April 2014. So, both ETSs had higher CEA prices at the initial operation stage, but the CEA prices decreased after the compliance period in the second calendar year.

3.4 Multivariate Regressions for City-Level ETSs

We ran multivariate regressions for the three better operated city-level ETSs, Beijing ETS, Shanghai ETS and Shenzhen ETS, as shown in Table 9. The dependent variables are the CEA price returns ($lnReturn_t$) of Beijing, Shanghai, and Shenzhen respectively.

It was found that the one week lagged Brent oil price return ($D.lnBrent_t$) had a short-term positive effect on Beijing CEA price at 5% significance level. It indicates that the increase of oil price led to the short-run increase of Beijing CEA, as enterprises would substitute coal for oil to some extent, resulting in an increase in

emissions and CEA demand. And, according to the joint F test, changes in oil price granger cause changes in CEA price of Beijing at 5% significance level. Additionally, the changes in stock index displayed a weakly positive effect in Eq.2 of Beijing ETS. It implies that the increase in stock returns, as a sign of future economic growth, drives the industrial output and the associated emissions, which raises CEA price.

With respect to Shanghai, the lag order one of the coal price returns had a negative effect on CEA price returns, which is similar to Beijing but more significant. And, the F-test indicates that changes in coal price granger cause changes in Shanghai CEA price. In the contrast, the 1 week lagged LNG price return ($D.lnLNG_t$) displayed a significantly positive effect on CEA price returns. The result meets our expectation based on the substitution theory that CEA price increases when LNG is substituted by cheaper and carbon-intensive fuel such as coal. No Granger causality was found between LNG price and CEA price based on the joint F-test. Eq.3 shows a slight Granger causality from stock returns to CEA price returns.

The regressions for Shenzhen ETS found no significant relations between CEA price and energy prices. However, there was a significant short-run effect of stock returns on CEA price return with a two-week lag. The positive coefficient implies that CEA price would increase under good economic conditions due to more economic output and the associated emissions. The joint F-test also indicates a significant Granger causality from stock returns to CEA price returns.

Further, we can see from Table 9 that Beijing, Shanghai, and Shenzhen all experienced a decrease in CEA price returns after *Break2014*. This is similar to the previous finding that the piloting ETSs had higher level CEA prices at the beginning of their establishment in 2013, but displayed significant decreases of the prices after the compliance break in the second calendar year (2014). However, Shanghai CEA price increased after June 2016 and Shenzhen CEA price increased after June 2015 which may be caused by the demand from new entrants.

4. Discussion and Policy Implications

In general, as newly born markets, the local ETS markets in China face thin trading and volatile price. One reason is the low market liquidity. It may be difficult for a seller of CO_2 emission allowances to quickly find a buyer that they want to make the transaction with. And, some entities with allowance surplus may want to keep the allowances for their own use in the next compliance year rather than selling them. In China, the spot trading is allowed, but derivatives trading is off-limits. This limited type of commodities in the market in addition to firms' lack of understanding and capacity of playing in the ETS market can also be the reasons for a dearth of actual trading.

The local CEA prices are far less than the ideal prices that can cause substantial low-carbon actions. The prob-

lem of low-level pricing happens at other existing ETSs as well. As a comparison, the EUA price in EU-ETS during Phase II (2008–2012) was about 23.64 $/ton CO_2e on average (Daskalakis 2013). Nonetheless, it decreases to a low level in Phase III (2013–2020). For instance, the EUA price was only about 8$/ton CO_2e in April 2015 and about 6$/ton CO_2e in April 2016 (World Bank 2015; 2016), which were similar to the level of the CEA price in Shenzhen ETS at that time. The low-level economic incentive from ETS was not able to encourage the regulated enterprises to invest in mitigation technologies in China (Yang, Li, and Zhang 2016). The enterprises rather considered participation in ETS as an approach to enhance public image and the ties with governments (Yang, Li, and Zhang 2016). However, a market-based policy instrument like ETS tends to be more acceptable by enterprises than the traditional command-and-control approach (Liu et al. 2013). Also, ETS mobilized a large number of business actors (emitters and intermediaries), local officials and researchers to work on low-carbon strategies and activities. The cooperative governance network constructed during the process is likely to be necessary and more cost efficient for long-run emission reduction in China.

The price values of CEA and the level of trading activities vary across the ETS pilots, which is reasonable considering the differences in policy design, local governments' political will and local economic context. Among the city-level ETSs, Chongqing and Tianjin are not so market-oriented, with lower CEA prices and less active transactions. Loose enforcement, the oversupply of allowances and emphasis on local economic interests can be the reasons. An implication is that even though China is keen to develop the national ETS, it may work better in some regions than others at the local level.

When investigating into the Granger causality from energy prices to CEA prices, the findings varied among local ETSs, because of local differences in market dynamics of CEA and energy resources. We found no significant Granger causality from energy price changes to CEA price changes in the two provincial level ETSs, Hubei, and Guangdong. Regarding the city-level ETSs, we found a Granger causality from oil price changes to CEA price changes in Beijing. And, there was a positive effect of oil price changes on CEA price changes with the one-week lag. It implied a short-term substitution of oil with coal which is cheaper and more carbon-intensive. In Shanghai, we found a Granger causality from coal price changes to CEA price changes in Shanghai. And the coal price changes had a negative short-run effect on the CEA price changes, indicating that an increase in coal price drives a move away from coal toward less carbon-intensive fuels (e.g. natural gas or oil). It was also found that there was a positive short-run effect of LNG price changes on Shanghai CEA price changes, which is also consistent with the substitution theory. The scale of the short-run effect of LNG price is smaller than that of coal price. This is because the coal consumption makes up a larger portion of the energy consumption so that the chang-

es in coal price lead to greater changes in emissions and the CEA price. No Granger causality was found between LNG price and CEA price.

Additionally, we found a Granger causality from stock index changes to CEA price changes in Beijing, Shanghai, and Shenzhen. In Shenzhen, the Shanghai Shenzhen 300 stock index displayed a positive short-run effect on CEA price with a two-week lag. The same with Beijing. Therefore, the CEA price would increase at the times of economic prosperity, because the larger industrial outputs and the associated emissions can raise the demand for CEA. Further, the coefficients on break dummies show that all ETSs experienced a higher-level CEA price at the initial stage of operation but a decrease of the price after the compliance break in the next calendar year. The decrease in the CEA price could be because the demand for CEA decreased over time. So, policymakers need to consider strengthening the CEA allocation to reduce the CEA supply and increase the CEA demand, in order to keep a high-level CEA price.

Overall, this study contributes to our understanding of ETS (or other tradable permit policies) by adding empirical evidence in the context of China. The local ETSs set good examples of institutional innovations when adopting ETS and their performances show how ETS works in regions under different development stages. Our econometric analyses highlight that energy prices have significant influences on CEA prices, but the influences are different across local ETSs. In future, for either local ETSs or the national ETS, policymakers and investors should be aware of the dynamic relationships between the energy markets and CEA markets to reduce the CEA price volatility caused by the fluctuations of energy prices. A big problem of the ETSs is that the CEA price is too low. So, when coal price increase, or when LNG price and oil price decrease, the regulators can somehow buy in allowances to prevent CEA price from dropping, especially if the CEA price is low. Another implication is that policies promoting the use of cleaner energies (e.g. natural gas) or general energy efficiency programs may reduce CEA price. Such policies should be followed by methods to shorten CEA supply or increase CEA demand.

China's National Development and Reform Commission (NDRC) has announced its *Plan for Building the National Carbon Emission Trading Market for Power Generation Industry* on 18 December 2017. It says China will take about one year to complete the emission exchange system and take another one year to try out the allowance allocation and trading before it officially operates the national ETS. We can expect that it will be very challenging for China to operate ETS at the national level, considering the performance diversity of the local ETSs at the piloting stage. The differences in CEA prices between local ETSs, to some extent, reflect the differences in local marginal abatement costs. It is practical to start with a single industry sector and brings in more sectors when the institutional design is more mature and the measurement, reporting and verification (MRV) system

is more complete. However, the power generation sector has faced with many other policies, such as renewable energy promotion policies. The coordination of the policy mix is important.

The integration of the local ETSs into the national ETS will be challenging too. For instance, the sectoral coverage of the national ETS is different from the current local ETSs. NDRC's solution is that the national ETS will regulate the power generation sector and gradually take in other sectors. Meanwhile, the local ETSs will continue to operate until the national ETS is fully functional. However, the standards for identifying the potential participants are different between the national level and the local level. For example, Shenzhen includes industrial enterprises that have annual emissions larger than 3000 tons CO_2e, but the standard set at the national level is 26000 tons CO_2e annually, which means that some enterprises regulated by Shenzhen ETS may not be regulated by the national ETS. These regulatory uncertainties will discourage the current participants in local ETS from actively engaging in the market or taking low-carbon actions. The standards at the national level should be stricter than those of the local ETSs and consistent political support is crucial (Bolun et al. 2018). The central government should offer guidelines and methodologies on design and operations of ETS regarding coverage and scope, MRV, allowance allocation and enforcement, while the local governments should be given discretion with implementation taking into account local contingencies (Bolun et al. 2018).

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