Dynamics of regional carbon markets in China

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Abstract

This paper describes the market architecture of five regional carbon markets in China and carries out an empirical analysis of carbon spot price co-integration from 2014 to 2019. The evidence of co-integration at rank one reveals that these regional ETS pilots are not mutually exclusive of each other. The empirical results in this study show, for the long run, each percentage-point increase in Shanghai and Hubei pilot will cause a decrease of 0.37% and 0.78%, respectively, in the Guangdong price while Beijing and Shenzhen ETS do not enter the long-run relation significantly. In the short term, results suggest that any deviation from the equilibrium co-integrating relationships is mainly caused by changes within the Guangdong ETS. Given the critical stage of development of the national ETS, greater attention should be paid to exploring the relevance of carbon prices across pilots and eventually connecting the regional pilots to the national ETS.

Keywords: Carbon markets; China's regional emissions trading; Emission allowances; Market architecture; Cointegration, Vector Error Correction.

JEL Classifications: C32; E44; R11; Q43.

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1. Introduction

China accounts for the largest share, which represents 28% of the world's total greenhouse gas emission[1] (IEA, 2020). The scale and growth of industrial activities and energy consumption in China explain the high level of emissions. In September 2020, China announced ambitious goals for sustainable energy and carbon neutrality by 2060, and to curb peak carbon emissions by 2030 (People's Republic of China, 2020). With increasingly stringent energy-saving goals, green technologies, ongoing climate mitigation and adaptation, China aims to reduce carbon emissions by about 70% from the current level by 2050 (Energy Foundation China, 2020). In the past, China has mostly relied on administrative tools to reduce carbon emissions. Achieving "carbon neutrality" through administrative means can be effective but also costly and inefficient. The National Development and Reform Commission of China was aware of this dilemma, and this was reflected in the plan to launch the regional and national emission trading schemes for 2013 and 2021 respectively (People's Republic of China, 2016).

In 2013, the Chinese government introduced a pilot emissions trading scheme by establishing six regional carbon markets: Beijing, Shanghai, Guangzhou, Tianjin, Hubei, and Shenzhen. Chongqing ETS was added in 2014 and Fujian ETS started trading in 2016[2]. The pilot areas cover a range of different economic circumstances and average levels of energy use and emissions differ greatly. By the virtue of the price mechanism and legal construction divergence, the regional markets represent disequilibrium states. The national Emissions Trading System, which include

1 The International Energy Agency (IEA) estimates carbon dioxide emissions from the combustion of coal, natural gas, oil, and other fuels, including industrial waste and non-renewable municipal waste.

2 Fujian ETS is relatively new compared to the other ETS pilots. Chongqing and Tianjin ETS are the most illiquid carbon markets among the pilots. This study does not discuss these three markets.

2,225 enterprises in the power sector, was expected to trade 2.5 billion tons of emission allowances, or 30% of China's national emissions for the first pilot year (World Bank, 2021). China's national ETS would thus surpass the EU ETS and become the world's largest carbon market in terms of total traded volumes. Initially, the regional ETS groups would operate in parallel to the national ETS, but in the long run would be integrated into the national ETS. In addition, the ambitious 'carbon neutrality' target has accelerated the development of regional and national ETS in China. To accomplish the objectives, China's growth of the carbon market integration is a necessary and feasible step.

Despite the progress made so far, having little experience in market-oriented instruments and a shortage of professionals, China differs from other developed jurisdictions that have mature emission trading schemes. The need to further increase political and public acceptability of carbon pricing is critical. China is a large, populous, and diverse country and the performance of its carbon and energy markets has regional, national, and global effects. Along-term goal for developing emission-trading schemes at the regional level is to create a single integrated market with comparable pricing across provinces in China. Linking emission markets would encourage more participants and create a larger market with cheaper carbon reduction options. A concern with not linking the ETS is, that can lead to carbon leakage or carbon price pass through; the 'greener' regions with higher carbon abatement costs would push the emission-heavy production to the regions that do not have an ETS or have ETS with lower prices.

Examining the relevance of carbon prices across provinces is beneficial not only for mutual learning among ETS pilots, but also for the establishment of a national ETS and, eventually, connecting the domestic carbon markets to international carbon markets. Several reasons have been postulated for the growing interest in regional ETS integration: the increased flow of capital across provincial boundaries due to the relaxation of controls on non-institutional participants and investors; improvements in the flow of information; and the potential gains from diversification of investments on an international level. Arbitrage activity should maintain the prices of perfect substitutes trading on separate markets tightly linked. (Mizrach, 2012). Notably, disjoint regional markets have caused market inefficiency, increasing the difficulty of linking to the national market. Therefore, it would be of some importance to analyse the dynamic fluctuations (in terms of lead-lag relationships) of the emerging regional carbon markets in China. This paper presents a comparative exposition of how the dynamics of these regional carbon markets are propagated and whether these linkage patterns change in response to the movements of a more established market.

The contribution of this paper is threefold. First, to the best of my knowledge, this is the first study investigates the relationship between carbon prices of five ETS – Beijing, Shanghai, Guangdong, Shenzhen, and Hubei in China, using the co-integration technique and vector error correction model with restriction tests. Second, by using more recent data, from 2014 to 2019, the overall results add important empirical evidence to the literature. Third, the insight into economic and energy structure in the five major regions of China is important for improving the richness of the carbon market architecture analysis.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on emission trading schemes globally and domestically. Section 3 presents the market architecture in China's regional carbon markets, allocation methods, and regulation. Section 4 presents the methodology and models to estimate the spillover effects among different regional ETSs in China.

Section 5 describes the data used in this study. Section 6 discusses the empirical results. Section 7 is conclusions with policy implications.

2. Literature review

ETS is an organized market designed to achieve specific policy objectives. In this case, the goal is to limit carbon emissions. The absence of such a mechanism (that is, a lack of market incentives) could let low efficiency continue, delay the adoption of clean energy practices, risk a shortage of energy, and even allow corruption in regulation of emissions. The combination of all that means more pollution. The literature includes a range of market models where participants interact. As the most preferred quantitative tool, statistical models such as Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH), Vector Auto Regression (VAR), and Vector Error Correction (VEC) models are frequently adopted to study ETS carbon prices and influencing factors. Under an ETS, the price of carbon spots in the secondary market is unstable and is easily affected by weather, disasters, energy markets, and arbitrageurs. Extensive research has been carried out on the EU ETS, since it is by far the largest, most liquid, and most developed carbon market (Alberola et al., 2008; Bunn and Fezzi, 2009; Paollela and Taschini, 2008; and Zhang and Sun, 2016). Daskalakis et al. (2009) and Benz and Trück (2006) provide some of the first econometric investigations of the new emission allowances' behaviour. Bunn and Fezzi (2009) use a structural cointegrated VAR model to address the EU ETS's economic impact on carbon, wholesale electricity, and gas prices. The VAR and VEC models have been pursued in related cross-border energy and carbon markets, or different carbon-related products (Bredin et al., 2014; Mizrach, 2012). Mizrach (2012) analyses the market architecture and common factors of emission reduction instruments in Europe and North America. This paper provides the most insightful concept regarding our study.

Researchers have started to conduct qualitative and quantitative studies in China's regional carbon markets. (Jotzo and Löschel, 2014) reviewed the behaviour of China's ETS pilots in their first compliance year, pointing out that the ETS pilots did not have clearly defined emissions targets. Secondary carbon market prices suffered from the inconsistent standard regionally and over-allocation. (Zhang et al., 2014) emphasized that a clear legal mandate at the national level is important for developing regional ETS pilots. Financial penalties for non-compliance cannot be altered without changing the laws. Notably, in the absence of national law, the provinces and sub-provinces would not have strong incentives to engage in emission trading. Zhang, (2015) stated that educating the covered entities and ascribing allowances as financial assets are crucial in addition to constructing the market. Zhang and Andrews-Speed (2020) thoroughly analysed the difficulties in building ETS in China from an institutional perspective. They argue that monopolies in China's state-owned energy enterprises impede the development of regional and national ETSs. The central and provincial governments have a substantial onus to reform the energy markets in order to unbundle the monopolies, to further develop ETSs in China.

Regarding quantitative empirical analysis, the previous research focused primarily on correlations between energy and carbon markets. Zhang and Zhang (2016) adopts a quantile regression approach to analyse the relationship between energy prices, economics growth, temperature and Shanghai's carbon price. Chang et al. (2018) investigated the dynamic linkage effects between energy and emission allowance prices for China's regional ETS pilots using cointegration techniques. The main focus of Chang's paper was the interaction between energy product price and emission price, the authors do not discuss the interactions between the regional ETS pilots, neither in the long run nor the short run.

A recent study by Wang et al. (2021) investigate the long-run cointegration relation between the EU ETS and China's regional ETS by choosing five regional ETS in China and one EUA price series. They found long-run cointegration among the markets. However, they did not include Shanghai ETS in the analysis. Instead they use Tianjin ETS data which only contains 34 monthly observations.

3. China's regional ETS market architecture

There are differences in natural resources and climatic features among five jurisdictions in this study, as well as significant differences in economic development, energy market structure, and residents' willingness to offset carbon emissions. Beijing, Shanghai, Shenzhen, and Guangzhou are the four most economically powerful cities in China and in the forefront of China in terms of GDP growth. The increase in energy intensity associated with economic expansion has also increased carbon emission intensity. These four cities, each with its unique characteristics, are actively exploring the carbon markets. Hubei Province is relatively less developed but is representative of the national average, with an economic structure dominated by heavy industry (Jotzo and Löschel, 2014). The current allowance allocation in Chinese regional ETSs highly relies on grandfathering and benchmarking (history-based methods), similar to phases 1 and 2 (2005-2012) in the EU ETS. Even though China's pilots attempted an auction mechanism to allocate the allowances, the primary objective appears to be to reduce the price to attract more participants, with social welfare having a lower priority. In terms of a carbon secondary market, the price of emission allowances was volatile around the compliance deadlines, which signals a cyclical behavior across all the Chinese ETS pilots. For the rest of the year, however, the ETS pilots were illiquid, with few transactions taking place. The cyclical price behavior in carbon trading has mainly reflected the ETS compliance function. The motivation of regulated units to spontaneously reduce carbon emissions is relatively weak. Table 1 summarises the main differences among regional ETS pilots.

3.1 Beijing ETS

Beijing is the center of the country's economy, culture, and foreign relations. Its urban strategic positioning necessitates vigorously promoting ecological construction and improving environmental quality. Beijing ETS was designed at the top level, taking the lead in defining the legal framework and effectiveness of a carbon trading system at the local level (Beijing Municipal Commission of Development and Reform, 2013) Beijing's carbon trading products are diverse and include not only local allowances and carbon offset products but also forestry carbon sink projects and energy-saving emission reductions. Given the concern that over 65% of total electricity consumption in Beijing is imported from other provinces, indirect emissions from electricity generation both within and outside the Beijing are covered in Beijing ETS (Feng et al., 2013). Since 2014, the Beijing ETS has pioneered cross-regional carbon emissions trading, and prioritizes cross-regional trading with Hebei Province and Inner Mongolia Autonomous Region. Beijing and Shenzhen are the only ETS pilots regulated by their municipal legislators, which provides higher legal regulation stability. In comparison to other regional ETSs, Beijing ETS has a relatively high carbon price and a relatively small trending change, which is conducive to encouraging businesses to contribute to energy conservation and emission reduction.

3.2 Shanghai ETS

Located in the Yangtze River Delta, Shanghai is the country's most vibrant commercial and financial hub (Development Research Center of the State Council and World Bank, 2013). It has progressed in green economic growth, technological industry development, and carbon market development. The energy production of the city still includes coal, but in a far smaller proportion than at the national level. Shanghai took the lead in building pilot carbon trading in 2011 and officially launched the Shanghai ETS in November 2013. At its inception, Shanghai ETS established the most detailed and thorough report and regulation guidance of all China's ETS pilots (Shanghai Municipal Bureau of Ecology and Environment, 2021). However, the legal foundation of Shanghai ETS is relatively weak and incomplete. With the launch, the Shanghai ETS is the only pilot in China to have achieved 100% compliance for continuously seven years. It has now covered 57% of the city's emissions. Building a complete measurement, reporting, and verification and legal framework tailored to its region would be the next challenge for Shanghai ETS. In 2021, the trading platform for the national ETS was launched in Shanghai.

3.3 Guangdong ETS

Guangdong province hosts major port facilities on the South China Sea and is a prominent channel for both domestic and international transportation and trade. Its annual global trade volume accounts for nearly a quarter of China's total. Connected to its active and wide-ranging economy, the Guangdong ETS has a high level of freedom and openness. It was the first pilot[3] opened to foreign investors and it allows unincorporated organizations, such as funds and trusts, to trade in its markets. The Guangdong ETS has become China's largest carbon trading center with

[3] Guangdong ETS and Shenzhen ETS now are both open to foreign investors. Shenzhen is a major city in Guangdong province. Shenzhen ETS and Guangdong ETS operate in parallel.

the largest market share and increasing liquidity. It is currently trading over 60% of the province's emissions (ICAP, 2020). Guangdong ETS has gradually established a multi-level market system in which the primary and secondary markets interact with each other. At present, Guangdong ETS has successfully organized 16 allowances auctions, with an auction revenue of about 800 million yuan, which signals an occurrence of a mature carbon market. Its auction design is exceptional among all pilots. In addition, the Guangdong ETS is close to completing third-party verification regulations.

3.4 Shenzhen ETS

Shenzhen ETS pilot has legislative authority over its own territory, and was the earliest ETS pilot running in China, in 2013. The main regulated target of Shenzhen ETS is corporate organizations rather than facilities. The government has designed dual emission reduction targets — an absolute cap target for whole regulated industries, and relative emission reduction targets for each of the control units (Shenzhen Municipal Bureau of Ecology and Environment, 2021). The total absolute emission cap can be increased year by year, but the carbon intensity for each participant, and the overall average carbon intensity target, need to be decreased over time. To encourage enterprises in tertiary industry to participate in carbon trading, the initial inclusion threshold for Shenzhen ETS is quite low at 3000 $tonCO_2/year$, even lower than Beijing's (5,000).

3.5 Hubei ETS

The economic growth rate, the share of primary, secondary and tertiary industries, and the overall energy structure of Hubei Province are reflective of China as a whole country (Qi et al., 2014). In comparison to the other four pilots, Hubei is more representative of a wide range of provinces in China, being strongly reliant on secondary industries and coal consumption, while the inflexible demand for energy consumption continues to develop at an exponential rate. The Hubei ETS pilot prioritizes stability above development. It is provincial in scope, encompassing numerous administrative levels ranging from urban to rural. The Hubei ETS, begun in 2014, quickly became one of the most active ETS pilots, with the highest traded volume and turnover rates among all regional pilots over its first two compliance years. Hubei ETS went on to increase its scope of regulated sectors in subsequent years, including the ceramics, food, and beverage industries (People's Government of Hubei Province, 2014). In the beginning, the entry requirement for Hubei ETS was that each participant must emit at least 60,000 tons of CO_2 per year. That threshold has been lowered to 10,000 tons. Hubei ETS has a great diversity of market participants, including energy companies, institutions, and individual investors. In 2020, Hubei ETS took on the mission of establishing the registration system for national ETS.

3.5 Summary

Even though Chinese regional ETSs have been in operation for some years, some market design details have not become uniform and finalized. The regional markets vary in design, participating industries, allocation methods, trading products, and market threshold. These features isolate the regional markets from each other. It is important to note that the carbon transactions in the pilots are predominantly intra-provincial. Consequently, while China's regional ETS's have achieved compliance, the price discovery function has not yet matured. Heterogeneous regional markets struggle with carbon price fluctuations, over-allocation of free allowances, low liquidity, and inadequate regulation systems. Emission allowances are mainly issued by free allocation, but the free allocation method has resulted in inefficiencies, political misallocation, and bureaucrat interference.

Table 1.
Market architecture – Differences among regional ETS in China

	BEIJING	*SHANGHAI*	*SHENZHEN*	*GUANGDONG*	*HUBEI*
ETS Covered Emissions of the Jurisdiction's Total	40%	57%	40%	60%	45%
Number of Regulated Firms	903	298	794	279	338
Involved Industries	Industrial and non-industrial entities; qualified enterprises, and individuals	Airports, chemical fibers, power and heat, water suppliers, hotels, textiles, etc.	Power, water, gas facilities; manufacturing sectors; port and subway sectors; transport sectors.	Power, iron and steel, cement, papermaking, aviation, and petrochemicals	Power and heat supply, iron and steel, metal, etc.
Allocation	Free Allocation; Auctioning up to 5%	Free Allocation; Auctioning	Free Allocation; Auctioning	Free Allocation (95% for power generation, 97% for iron, aviation, and cement); Auctioning	Free Allocation; Auctioning
Carbon Products	BEA, CCER, and Forest Carbon Sinks	SHEA, CCER, and Forest Carbon Sinks	SZEA, CCER, and Forest Carbon Sinks	CDEA, CCER, and Forest Carbon Sinks	HBEA, CCER, and Forest Carbon Sinks
Entry Condition	Over 5,000 tonCO2/year	Over 20,000 tonCO2/year (industrial enterprises); over 10,000 tonCO2/year for other enterprises	Industrial enterprises over 3,000 tonCO2/year, large public building project 10,000 square meters	Over 10,000 tonCO2/year (industrial enterprises); over 5,000 tonCO2/year for service industry	Over 10,000 tonCO2/year energy consumption

Source: Own elaboration based on data from Emission Trading Worldwide: Status Report, by International Carbon Action Partnership, 2020. Retrieved from https://icapcarbonaction.com/en/publications. And from Wind Database. Retrieved from https://www.wind.com.cn/en/edb.html.

Notes: BEA stands for Beijing Emission Allowances, SHEA for Shanghai Emission Allowances, SZEA for Shenzhen Emission Allowances, GDEA for Guangdong Emission Allowances, and HBEA for Hubei Emission Allowances. CCER for China Certified Emission Reduction; it is a carbon offset product that can be traded in regional ETSs. M stands for million.

4. Methodology

The co-integration among the CO_2 emissions products of different regional environmental exchanges describes how markets, each of which might be non-stationary, may nonetheless be linked. Engle and Granger (1987) pointed out that most of the macroeconomic variables may be non-stationary through time. It is expected that non-stationary price variables could be bound together and converge to some stationary processes by long-run equilibrium relationships. The multivariate Vector Auto-Regression (VAR) model is a system regression model with multiple endogenous variables; it is a reformulation of the covariance of my data, with two covariances discussed in the model: (i) the covariance between the variables at time t; (ii) the covariance between time t and time $t-h$. This model allows us to analyse both the short-run and long-run dependencies of these variables. The definition of the model starts with the data matrix $x_t = [x_1, x_2, x_3, x_4, x_5]'$ where x_t is a *(*5×1*)* vector of emission allowances prices. The unrestricted VAR *(p)* model was estimated based on the following:

$$x_t = \Pi_1 x_{t-1} + \Pi_2 x_{t-2} + \cdots + \Pi_p x_{t-p} + \varepsilon_t \qquad (1)$$

$$t = 1, \dots, T \; ; \; \varepsilon_t \sim IN_p \; (0, \Omega)$$

$\Pi_1, \Pi_2 , \dots , \Pi_p = p \times p$ are coefficient matrices, p denotes the number of lags chosen to ensure no serial correlation in the residual ε_t. Equation (1) shows the reduced form of the model since it described only the variation in x_t as a function of lagged (past) values of the process, but failed to capture the current values. This information about current effects in the data is contained in the residual covariance matrix Ω.

Johansen (1988), Johansen and Juselius (1990), and Juselius (2006) used likelihood ratio tests based on a VAR estimation and provided a vector equilibrium correction (VEC) model. This method is estimated by the full information maximum likelihood as suggested in Johansen (1988). The VEC model gives a reformulation of Equation (1) in terms of differences, lagged differences, and levels of the process, which naturally classified the relationship into short-run and long-run effects. Following Johansen (1988), p_t can be appropriately implemented to the error correction model with k-1 lags; and p_t represents a vector of p nonstationary endogenous variables. The error correction formulation for VAR (p) is described as:

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \Gamma_2 \Delta x_{t-2} + \cdots + \Gamma_{p-1} \Delta x_{t-p+1} + \Pi x_{t-1} + \varepsilon_t \qquad (2)$$

In Equation (2), the matrix Π contains information about the long-term relationship among endogenous variables, and the rank of $\Pi(\mathrm{r})$ is the error correction (ECM) term, the lag placement of the Error Correction (ECM) term is 1. Either $\Pi = 0$, or it must have reduced the rank: $\Pi = \alpha\beta'$, where α denotes the estimation on the speed of adjustment to the equilibrium, and β denotes the cointegration vectors. Both α and β are $\mathrm{n} \times \mathrm{r}$ matrices, r is the rank of Π and the number of co-integrating relations, in order to make Equation (2) a stationary process. ε_t is the error term. With the co-integration $\Pi x_{t-1} = \alpha\beta^T x_{t-1}$, the linear combinations $\beta^T x_{t-1}$ should be stationary and could be interpreted as deviations from long-run equilibrium; the matrix α is the adjustment speed coefficients. Thus, the cointegrated VAR (p) model is given by:

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \Gamma_2 \Delta x_{t-2} + \cdots + \Gamma_{p-1} \Delta x_{t-p+1} + \alpha\beta' x_{t-1} + \varepsilon_t \quad (3)$$

where $\beta' x_{t-1}$ is the error correction term that shows the long-run relationships between five variables. The likelihood ratio test – the trace test — is used to test the correlations (co-integration rank) between variables, which are shown in Equation (4):

$$\lambda_{trace}(r_0) = -T\sum_{i=r_0+1}^{j} \ln\left(1-\hat{\lambda}_i\right) \quad (4)$$

The null and alternative hypothesis is the number of co-integrating vectors are less or equal to r_0 against a general alternative. The larger the $\hat{\lambda}_i$, the more stationary is the relationship. More specifically, if variables are not co-integrated, the co-integration rank, r_0, equals to zero, and $\ln\left(1-\hat{\lambda}_i\right) = 0$, λ_{trace} equals to zero. Interventions and market reforms frequently show up in energy markets, especially for early-stage carbon markets, as they are market-driven tools based on policies. This paper uses transitory dummies to account for transitory shocks in the markets, and then the reformulated model is expressed as Equation (5):

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \Gamma_2 \Delta x_{t-2} + \cdots + \Gamma_{p-1}\Delta x_{t-p+1} + \alpha\beta' x_{t-m} + \Phi_{tr} D_{tr,t} + \varepsilon_t \quad (5)$$

where the $\Phi_{tr} D_{tr,t}$ is a set of transitory (dummy) variables.[5] And these transitory shock dummy variables are defined as follows:

$$\Phi_{tr1} = \begin{cases} -1 \\ 1 \end{cases}, \quad \Phi_{tr2} = \begin{cases} 0.5 \\ -1 \\ 0.5 \end{cases}, \quad \Phi_{tr3} \begin{cases} 0.5 \\ 1 \\ 0.5 \\ -2 \end{cases}, \quad \Phi_{tr4} = \begin{cases} -1 \\ -0.5 \\ 0.5 \\ 1 \end{cases}, \quad \Phi_{tr5} = \begin{cases} 1 \\ -0.5 \\ -0.5 \end{cases}, \quad \Phi_{tr6} = \begin{cases} 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \\ -2 \end{cases} \quad (6)$$

The important fact of transitory dummies is that they sum to zero over time, so they do not have any effect on asymptotic distributions on the trace tests. It turns out later that there are six events where we need the six transitory dummies, and they will be defined when we use them (see section 6.2 below). The VAR (p) model can be given different parametrizations without imposing any binding restrictions on the model parameters and multicollinearity effects would present in those time-series data. There are tests available to test one at a time whether a specific variable

[5] Transitory .dummies are included to take care of transitory effects to the system cause by specific price shock. Φ_i is the corresponding coefficient (Juselius, 2004, chapter 6).

does not belong to the co-integrating vector. For instance, if we want to perform this restriction test for Beijing emission allowances prices, then the beta would look like zero while the other four betas remain the same. Thus, the long-run exclusion tests are conducted, these tests on restrictions on beta are done for a given choice of rank. If the restrictions are accepted, the variable can be omitted from the long-run relations, and the VAR model can be reformulated without losing information. The test of the same restriction on all beta is given in Juselius (2006), Section 7.2. For a test of long-run exclusion of one variable or two variables in the co-integration relations for $x_t' = [BEAPrice_t, SHEAPrice_t, GDEAPrice_t, HBEAPrice_t, SZEAPrice_t]$, the hypothesis is:

$$\mathcal{H}_1: \beta' = H \times \varphi = 0 \qquad (7)$$

where β' is $p1 \times \ p1$, H is $p1 \times s,\ \varphi$ is an $s \times r$ matrix of the unrestricted coefficients; and s is the number of unrestricted coefficients in each vector, $p1$ is the dimension of x_{t-1}' in the VAR model.

5. Data

This paper selects monthly data from the five regional ETSs from 28 April 2014 to 25 December 2019. Data sources regarding emission allowance prices are found in the following links: Beijing, https://www.cbeex.com.cn/; Shanghai, https://www.cneeex.com/; and rest from Wind Database, https://www.wind.com.cn/en/edb.html. Descriptive statistics for regional emissions allowances prices are presented in Table 2, and the five regional emissions allowances prices are plotted in Figure 1.

Table 2 indicates that Beijing emission allowances' maximum, minimum, and mean prices are the highest among all the ETSs. The overall average price of Beijing emission allowances was 56.8, 20 yuan higher than the second-highest average price, 30, in Shenzhen ETS. The volume traded in Shanghai ETS increased from approximately 1.47 million tons when it was launched in 2013 to 3.86 million tons in 2016. However, Shanghai ETS traded the smallest allowances amount across regional markets in 2018 and 2019. The Shanghai and Hubei emission allowances prices exhibit negative excess kurtosis while Beijing, Guangdong, and Shenzhen pilots show positive kurtosis. Hubei ETS has maintained the most consistent price and volume since its launch in 2014 (see Fig. 1). Table 2 confirmed that Hubei ETS has the smallest standard deviation, which indicates lower market volatility. Figure 1 shows some sharp reductions and some potential outliers exist in the series (third panel), signalling these series are more deterministic than stochastic. Given the policy-driven nature of these carbon markets, the practical implementation issues, such as the change of total cap setting, allocation method of emission allowances, and offsetting mechanism, will result in price fluctuations.

As regional carbon markets approached the compliance period, secondary market trading increased significantly, with carbon allowance spot prices falling to varying degrees. For instance, the Beijing carbon market experienced light trading following the compliance period that ended on 31 August 2018, with the average price falling by 20 (Chinese yuan) in September 2018 compared to August 2018. Between April and October 2014, the price of Guangdong emission allowances fell significantly due to a change in the minimum price setting in the carbon primary market. In September 2014, the Guangdong carbon market adjusted the reserve price for the primary market auction of carbon allowances from a minimum of 60 (Chinese yuan) in 2013 to 25-40. This significant adjustment mobilized the auction, which resulted in the secondary market price also falling to the reserve price level of the primary market auction due to the greater volatility of the auction reserve price compared to 2013.

Table 2. Descriptive statistics of allowances prices in regional ETS

Statistic	Beijing	Shanghai	Guangdong	Shenzhen	Hubei
Minimal price (Yuan/Ton)	37.3	4.7	10.4	7.0	12.5
Average price (Yuan/Ton)	55.0	29.7	19.7	31.3	22.4
Maximal price (Yuan/Ton)	86.8	44.0	69.7	72.8	38.9
Standard Deviation	11.87	10.86	12.17	13.99	6.50
Skewness	1.22	-0.92	2.51	0.88	0.46
Kurtosis	1.04	-0.32	5.89	1.44	-0.32
Pt (25)	49.6	24.6	13.6	24.3	16.3
Pt (75)	56.2	38.1	22.6	39.0	26.0

Source: Own elaboration based on data from China Beijing Green Exchange, Shanghai International Energy Exchange, China Hubei Emission Exchange, and Wind Database. Pt (25) is the first quartile. Pt (75) is the third quartile. Missing data were supplemented by Kalman Smoothing (Moritz and Bartz-Beielstein, 2017) since it provides minimum mean square error estimation and linear interpolation.

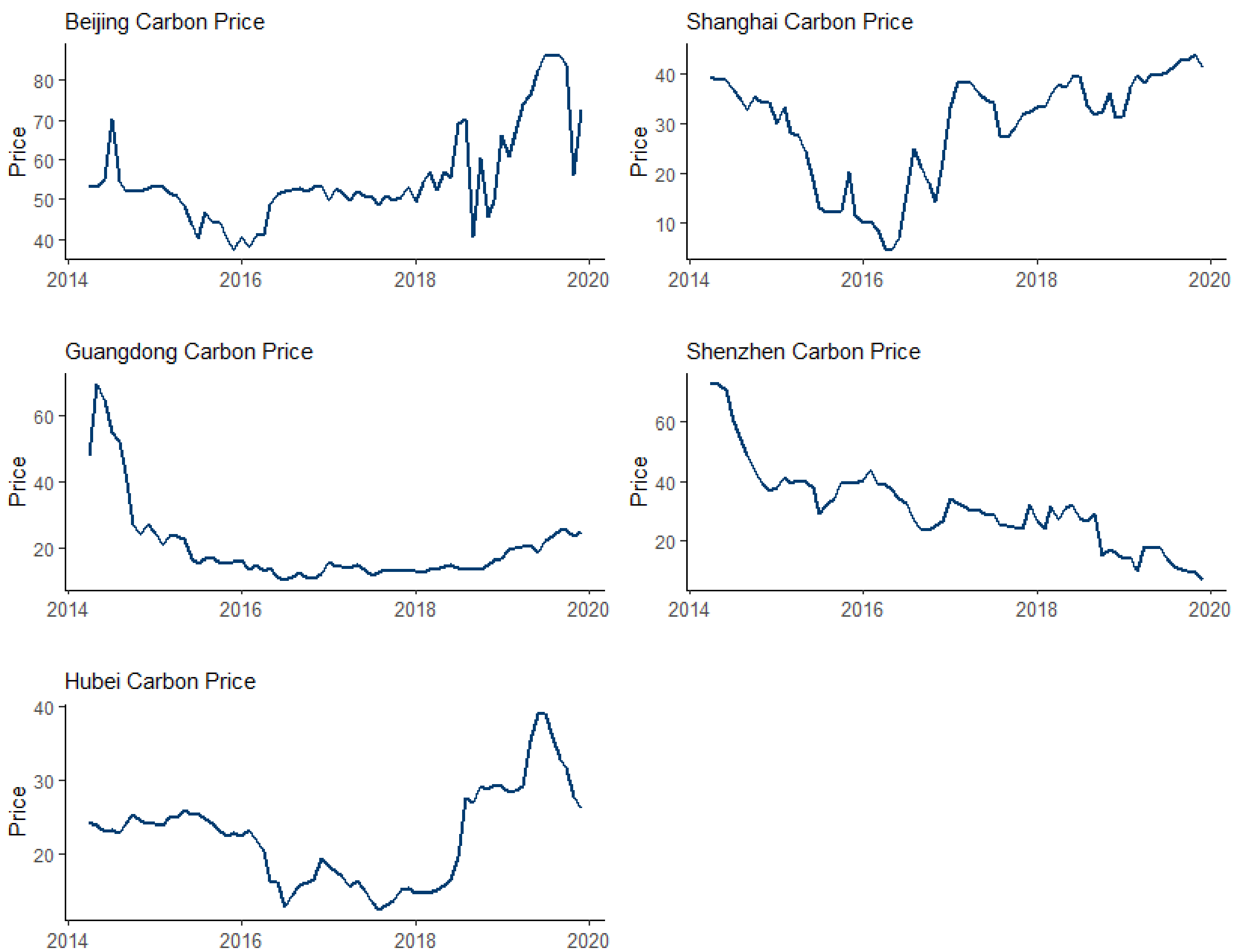

Figure 1. Average carbon monthly price from five regional ETSs from 2014.04 – 2019.12

6. Results and discussions

The model in this section is based on the monthly average price, with 69 observations from five regional ETS. The first diagnostic test of the co-integrated VAR model is to test for stationarity of the spot prices from regional ETSs by using the augmented Dicky-Fuller test (Dickey and Fuller, 1979), KPSS test (Kwiatkowski et al., 1992), and Zivot unit root test (Zivot and Andrews, 1992). Table 4 indicates that the five monthly series are nonstationary, but stationary in their first differences. We further examine the autocorrelations in the time series. The results (see Figure A2) show that the data are highly persistent in the sense that the autocorrelation decays to zero very slowly. Slow-decaying autocorrelation is considered as the signal for non-stationary time series. Thus, the variables are non-stationary and integrated of the same order, I (1).

6.1 Estimation of VAR model

Johansen's likelihood ratio tests for co-integration are sensitive to the lag length specification in the VAR model. The proper lag length at a VAR model should be determined to prevent spurious regression. To check the robustness of the results to the lag length specification, we tested the regression with lag 1, lag 2, lag 3, and lag 4 in the VAR model instead of automatically choosing by information criteria in the econometric software. Table 4 reports some diagnostic test statistics for the VAR models. Tests in Table 4 (a) cannot reject the null hypothesis of no ARCH effects at 5% significance level, which reveals that the data is not conditionally heteroskedastic. For VAR (1) and VAR (2), the null hypothesis of no autocorrelation cannot be rejected since the p-value of 0.06 is greater than the 5% significance level. However, for VAR (3) and VAR (4), the null hypothesis of no autocorrelation is rejected at 5% level. Both tests reject the normal distribution, zero skewness, and zero kurtosis at 5% level. The additive outliers in the series would be a reason that decreases the quality of the model.

Table 3.

Unit root test for carbon emission allowances price in five regional ETSs

Variables		BEAPrice	SHEAPrice	GDEAPrice	SZEAPrice	HBEAPrice
ADF	Drift	-1.6492 (AIC) Nonstationary	-2.2593 (AIC) Nonstationary	-2.596 (lag5) Nonstationary	-0.2484 (AIC) Nonstationary	-1.517 (AIC) Nonstationary
KPSS	Level	0.86*** Nonstationary	0.54** Nonstationary	0.59** Nonstationary	1.50*** Nonstationary	0.38* Nonstationary
Zivot	Trend	-3.7735 (lag1) Nonstationary	-3.8181(lag1) Nonstationary	-3.4603 (lag1) Nonstationary	-3.7018 (lag1) Nonstationary	-3.0857 (lag1) Nonstationary

(a) Unit root tests for original monthly data in level

Variables		BEAPrice	SHEAPrice	GDEAPrice	SZEAPrice	HBEAPrice
ADF	Drift	-7.9386 *** Stationary	-6.0017 *** Stationary	-6.1378 *** Stationary	-5.8979*** Stationary	-3.87*** Stationary
KPSS	Level	0.08 Stationary	0.13 Stationary	0.55 Stationary	0.13 Stationary	0.13 Stationary
Zivot	Trend	-8.6984 *** Stationary	-6.2325 *** Stationary	-8.063 *** Stationary	-6.3355 *** Stationary	-4.4091 * Stationary

(b) Unit root tests for first differenced monthly data

Notes: All the variables are in logarithmic form and at the monthly frequency.

*The t-statistics are reported. *** indicates significance at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 1% level.*

The critical values of ADF test are taken from Hamilton and Susmel, (1994) and Dickey and Fuller (1981). In the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, the null and alternative hypothesis are respectively stationary and not stationary. If type is set to "level" an intercept is added and if it is set to "trend" both an intercept and a trend are added. The critical values are taken from Kwiatkowski et al. (1992).

In the Zivot - Andrews test, the null hypothesis is that the series has a unit root with structural break(s), against the alternative hypothesis that they are trend/level stationary with break(s). The critical values are taken from Zivot and Andrews (1992). Lag 1 was chosen in the tests.

According to Equation (5), the inclusion of some transitory shock dummies is considered in the model to capture the impact of policy changes in regional ETSs. The six added dummy variables are included in the deterministic terms D_{tr}, and they are retained if they generate significant p values in the ARCH test, Serial test, and the normality test statistics.

Table 4.

Diagnostic tests of VAR (p) specifications for five regional carbon markets

Model	**k**	**ARCH test** p value	**Serial test** p value	**JB test** p value	**Skewness** p value	**Kurtosis** p value
VAR(1)	1	0.65	0.06	< 2.2e-16	0.02831	< 2.2e-16
VAR(2)	2	0.47	0.06	< 2.2e-16	0.03	3.167e-10
VAR(3)	3	0.60	0.01	5.581e-09	0.02	1.006e-08
VAR(4)	4	0.37	0.01	1e-11	0.00	4.388e-11

(a) Diagnostic tests for original monthly data in level

Model	**k**	**ARCH test** p value	**Serial test** p value	**JB test** p value	**Skewness** p value	**Kurtosis** p value
VAR(1)	1	0.79	0.41	< 2.2e-16	0.01	< 2.2e-16
VAR(2)	2	0.52	0.15	3.962e-13	0.37	8.438e-15
VAR(3)	3	0.45	0.01	7.568e-11	0.10	1.487e-11
VAR(4)	4	0.55	0.02	2.851e-09	0.00	1.46e-08

(b) Diagnostic tests for monthly data with six dummies

Note: The setting for the ARCH test allows multiple lag orders. JB is the Jarque-Bera test for normality of the residuals. All test statistics are asymptotically distributed as χ^2. The autocorrelation of the residuals is shown in Figure A2.

To account for the price fluctuation around the compliance deadline in Beijing and Guangdong ETS, Φ_{tr1} is included; Φ_{tr2} and Φ_{tr3} account for price fluctuations in Shanghai ETS; Φ_{tr5} and Φ_{tr6} account for price fluctuations in Guangdong and Hubei ETS respectively. Additionally, Φ_{tr4} is included to account for the carbon primary market floor price change in August 2014 — from 60 (Chinese) yuan/ton to 25-40 (Chinese) yuan/ton in Guangdong ETS. As such, six outlier dummies are defined:

$\Phi_{tr1} = 1$ for $t = 2018{:}09$, -1 for $2018{:}08$, 0 otherwise for Beijing ETS price;

$\Phi_{tr1} = 1$ for $t = 2015{:}06$, -1 for $2015{:}05$, 0 otherwise for Guangdong ETS price;

$\Phi_{tr2} = -1$ for $t = 2015{:}11$, 0.5 for $2015{:}10$ and $2015{:}12$, 0 otherwise for Shanghai ETS price;

$\Phi_{tr3} = 0.5$ for $t = 2016{:}04$, 1 for $2016{:}05$, 0.5 for $2016{:}6$, and -2 for 2016:07, 0 otherwise for Shanghai ETS price;

$\Phi_{tr4} = -1$ for $2014{:}08$, -0.5 for $2014{:}09$, 0.5 for $2014{:}10$, 1 for $t = 2014{:}11$, 0 otherwise for Guangdong ETS price;

$\Phi_{tr5} = 1$ for $t = 2019{:}03$, -0.5 for $2019{:}04$ and $2019{:}05$, 0 otherwise for Shenzhen ETS price;

$\Phi_{tr6} = -2$ for $t = 2018{:}08$, 0.5 for $2018{:}04 - 2018{:}07$, 0 otherwise for Hubei ETS price.

Diagnostic tests in Table 4 (b) reveal that with the inclusion of six transitory dummies, the ARCH test, serial test, and skewness tests improved, especially for VAR (1) and VAR (2). The null hypothesis of no autocorrelation cannot be rejected for VAR (1) and VAR (2) at 5% level. The VAR (2) model is the only one model that cannot reject the null hypothesis of zero skewness at 1% level. In general, the model is well-specified; only the normality of the series is not fulfilled. Considering the nature of the deterministic price series (rather than stochastic) and relatively small data sample, this is acceptable. Therefore, we proceed with tests with two lags and six dummies.

6.2 Cointegration test

Next, we perform the Johansen cointegration test using the trace statistics in order to test for the cointegration rank. It is clear that there is some evidence for cointegration in the sample period. The results are presented in Table 5.

Table 5.

Results of the Johansen co-integration unrestricted test

Null hypothesis	Alternative hypothesis	T statistic (with 6 dummies)	Critical value 5% level	Critical value 10% level
Trace statistics				
r = 0	r > 0	76.58**	70.60	66.49
r ≤ 1	r > 1	43.62	48.28	45.23
r ≤ 2	r > 2	23.16	31.52	28.71
r ≤ 3	r > 3	5.96	17.95	15.66
r ≤ 4	r > 4	0.08	8.18	6.5

*Notes: Monthly frequency. ** Denotes rejection of the null hypothesis at 0.05 level; * denotes rejection of the null hypothesis at 0.1 level. The first column in the table shows the null hypothesis.*

As can be seen in Table 5, the null hypothesis r = 0 gives a trace statistic of 76.58, which is significant at the 5% level. Thus, the null hypothesis of no co-integration is rejected. And the null hypothesis of $r \leq 1$ is not rejected at both 5% and 10% level as the trace test statistic is $43.62 < 45.23$. To conclude, the co-integrating tests above indicate that the rank is one, so we will move on with the rank of one. There might be indications of more robust integration of these markets if the co-integrating rank points firmly at two or more co-integrating relations.

The empirical results exhibit that emission prices of regional ETS pilots in China have equilibrium relationships in long term, but in the short term the five variables can be in disequilibrium. The long-run and short-run dynamic structure can be expressed as a vector error correction model (VEC) model. Thus, on the premise of the existence of one co-integration relationship, the VEC model can be further conducted.

6.3 Estimations of long-run co-integration relationships

To investigate the long-run co-integration relationship between emission allowances prices in regional ETSs, a VEC model is performed with rank one. Normalizing the co-integrating vector on Guangdong ETS prices, the estimated co-integrating coefficients are shown in Table 6 below. The co-integration equation can be expressed as Equation (8):

$$LGDEAPrice_{t-1} = -0.101 \times LBEAPrice_{t-1} + 0.45 \times LSHEAPrice_{t-1} + 0.171 \times LSZEAPrice_{t-1} + 0.877 \times LHBEAPrice_{t-1} \qquad (8)$$

From table 6, we conclude that the price of Beijing ETS shows negative relationship to Guangdong ETS while Shanghai, Shenzhen, and Hubei show positive to Guangdong ETS. The long-run emission price elasticity for Beijing, Shanghai, Shenzhen, and Hubei is respectively at -0.101, 0.45, 0.171, and 0.877. However, at this stage it is not clear whether all of the five prices are significantly in the long-run equilibrium relation. The Johansen and Juselius procedure allows me to test several hypotheses on the coefficients by imposing restrictions. Thus, we implement a restricted VECM to estimate the long-run impacts.

Table 6.

The restricted estimate of the co-integrating vectors $\boldsymbol{\beta}$ for r =1

Co-integrating Equations	Coef. ($\hat{\beta}$)
GDEAPrice (-1)	1.000
BEAPrice (-1)	0.101
SHEAPrice (-1)	-0.450
SZEAPrice (-1)	-0.171
HBEAPrice (-1)	-0.877
AIC	-1403.637
BIC	-1240.49
Log likelihood	300.474

Notes: Monthly frequency. Data are normalized to Guangdong emission allowances price.

The long-run exclusion tests are therefore conducted to check whether a variable included in the VEC model can be omitted in the long-run relationship. Coefficient estimates and significance levels associated with the tests of zero restrictions are shown in Table 7. The rejection of the null hypothesis means that the variable should be added to the co-integrating equation.

According to Table 7, the hypothesis of long-run exclusion cannot be rejected for both Beijing and Shenzhen emission allowances prices with p-value as high as respectively 0.90 and 0.59. A joint test $\mathcal{H}6$ also fails to reject the null that both Beijing and Shenzhen emission allowances price variables are not in the co-integration relation (χ^2 (2) = 0.78, p-value = 0.68). The hypothesis $\mathcal{H}2$, $\mathcal{H}3$ $, and$ $\mathcal{H}5$ are all rejected at 5% level; these results reveal that the long-run exclusion of Shanghai, Guangdong, and Hubei emission allowances prices in the co-integration relations are rejected. Thus, we concluded that Beijing and Shenzhen's allowances prices can be omitted in the long-run relation. Now it is clear that each percentage-point increase in the Shanghai emission allowances price will cause the decrease of 0.3712% in the Guangdong price, which is significant; and each percentage-point increase in Hubei emission allowances price will cause the decrease of 0.7801% in the Guangdong price significantly.

Table 7.

Tests of same restriction on all co-integration relations (r=1)

	Beijing	Shanghai	Guangdong	Shenzhen	Hubei
β_1'	0.101	-0.450	1.000	-0.172	-0.877
Restricted estimates:					
$\boldsymbol{\mathcal{H}1}$: $\beta_{BEAPrice} = 0$ $\mathcal{X}^2(1) = 0.02$ [$p = 0.9$] $\mathcal{H}1$ not rejected: Beijing can be excluded					
$\beta_1^{c\prime}$	0.000	-0.4323	1.000	-0.1956	-0.867
$\boldsymbol{\mathcal{H}2}$: $\beta_{SHEAPrice} = 0$ $\mathcal{X}^2(1) = 4.64$ [$p = 0.03$] $\mathcal{H}2$ rejected at 5% level					
$\beta_1^{c\prime}$	-0.8701	0.000	1.000	-0.021	-0.666
$\boldsymbol{\mathcal{H}3}$: $\beta_{GDEAPrice} = 0$ $\mathcal{X}^2(1) = 3.56$ [$p = 0.00$] $\mathcal{H}2$ rejected at 5% level					
$\beta_1^{c\prime}$	1.000	-0.130	0.000	0.367	-0.0234
$\boldsymbol{\mathcal{H}4}$: $\beta_{SZEAPrice} = 0$ $\mathcal{X}^2(1) = 0.29$ [$p = 0.59$] $\mathcal{H}4$ not rejected: Shenzhen can be excluded					
$\beta_1^{c\prime}$	0.478	-0.490	1.000	0.000	-0.8778
$\boldsymbol{\mathcal{H}5}$: $\beta_{HBEAPrice} = 0$ $\mathcal{X}^2(1) = 6.27$ [$p = 0.01$] $\mathcal{H}5$ rejected at 5% level					
$\beta_1^{c\prime}$	1.8845	-0.511	1.000	1.198	0.000
$\boldsymbol{\mathcal{H}6}$: $\beta_{BEAPrice} = \beta_{SZEAPrice} = 0$ $\mathcal{X}^2(2) = 0.78$ [$p = 0.68$] $\mathcal{H}6$ not rejected: Beijing and Shenzhen can be excluded					
$\beta_1^{c\prime}$	0.000	-0.3712	1.000	0.000	-0.7801

Notes: The null hypothesis is H_0*: a restricted linear combination of the vector process is stationary while the alternative hypothesis* H_1 *shows a non-stationary system, In order to test* $\beta_{GDEAPrice} = 0$*, we normalized the co-integrating vector on Beijing ETS price in* $\mathcal{H}3$.

In conclusion, there is long-run cointegration found in China's ETS pilot, but Beijing and Shenzhen ETS have been excluded in the long-run relation. Both Shanghai and Hubei ETS are in the long-run relation, and showed negative relation to Guangdong ETS's prices.

6.4 Estimations of short-run co-integration relationships

To focus on examining the short-run dynamics of the linkage effects among the five markets, the corresponding vector error correction model (VECM) is estimated for changes in the emission allowances prices. Table 8 provides the result of the analyses:

Table 8.

Estimation of the short-run and long-run equation

Variable Coefficients	ΔBeijing	ΔShanghai	ΔGuangdong	ΔShenzhen	ΔHubei
Error Corrections	-0.0023 (0.0468) [-0.050]	0.0657 (0.0743) [0.885]	-0.2169*** (0.0425) [-5.107]	0.0446 (0.0593) [0.752]	-0.0079 (0.0320) [-0.246]
ΔBeijing (-1)	-0.4606*** (0.1102) [-4.180]	0.3703** (0.1749) [2.117]	0.0801 (0.1000) [0.801]	0.4026*** (0.1395) [2.885]	-0.0540 (0.0753) [-0.717]
ΔShanghai (-1)	-0.0823 (0.0725) [-1.135]	0.1712 (0.1150) [1.489]	0.0859 (0.0657) [1.307]	-0.0008 (0.0918) [-0.009]	0.0715 (0.0495) [1.444]
ΔGuangdong (-1)	0.1416 (0.1160) [1.221]	0.1817 (0.1841) [0.987]	-0.0320 (0.1052) [-0.304]	0.1974 (0.1469) [1.344]	0.0183 (0.0793) [0.230]
ΔShenzhen (-1)	-0.0169 (0.0898) [-0.188]	0.1175 (0.1426) [0.824]	-0.0243 (0.0815) [-0.298]	-0.1991 (0.1137)* [-1.750]	0.0835 (0.0614) [1.360]
ΔHubei (-1)	-0.1604 (0.1959) [-0.819]	-0.4160 (0.3109) [-1.338]	-0.1413 (0.1777) [-0.795]	0.3823 (0.2481) [1.541]	0.3998*** (0.1340) [2.985]
Adjusted R-squared	0.3636	0.3215	0.2811	0.3035	0.21
Residual standard error	0.1083	0.1719	0.09825	0.1372	0.07406
F-statistic	3.734 on 14 and 53 DF	3.268 on 14 and 53 DF	2.871 on 14 and 53 DF	3.085 on 14 and 53 DF	2.272 on 14 and 53 DF

*Notes: Monthly frequency. The six transitory dummies are still in the model, they are just not shown in the result. *** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. T-statistics in square brackets []; Standard Error in parentheses ().*

As shown in Table 8, Guangdong is the only market in this system in which the error-correction terms are statistically significant. The error correction term in Guangdong emission allowances price is strongly significant at 1% level and negative, implying that when Guangdong's allowances price is disturbed by external factors and deviates from the long-term equilibrium, the error correction model will adjust it to the long-term equilibrium with a strength of -0.2169. The error-correction term is insignificant in the Beijing, Shanghai, Shenzhen, and Hubei ETS pilots but the test results confirm that Shanghai and Shenzhen pilots are influenced by significant short-run influences from lagged Beijing emission allowances prices, respectively, at 5% and 1% significance levels. Beijing seems to be led by changes in the lagged Beijing emission allowances prices at 1% significance level. Hubei is only affected by changes in the lagged Hubei emission allowances prices (significance at 1% level).

In summary, Beijing's, Hubei's, and Guangdong's emission allowances prices remain unaffected by any short-term effect from other regional ETS pilots. Both Shanghai and Shenzhen seem to be led by changes in lagged Beijing emission allowances prices. The lagged emission allowances prices in the Beijing and Hubei ETS pilots have significant impact on their current emission allowances prices.

6.5 Discussion

This paper describes the market architecture of China's pilot carbon markets and carries out an empirical analysis of market co-integration in China from 2014 to 2019. The concept of co-integration among a set of emerging regional carbon markets in China is used to test whether they shared any degree of long-run integration with each other. Not only does this procedure provide a platform for performing detailed static analysis, it also takes advantage of the restricted Vector Error Correction Model to estimate both short- and long-run relationships' impacts of the emission allowances prices from regional pilots. The evidence of co-integration at rank one reveals that these separated regional ETS pilots are not mutually exclusive of each other and that market integration is feasible. Based on the empirical results above, some main conclusions are obtained as follows: First, it is noteworthy that the Beijing and Shenzhen ETS pilots do not enter into the long-run relationship significantly. For the long-run, each percentage-point increase in the Shanghai and Hubei emission allowances price will cause a decrease of 0.37% and 0.78%, respectively, in the Guangdong price. Second, in the short run, the parameters in the VECM suggest that any deviation from the equilibrium co-integrating relationships is mainly caused by changes within the Guangdong ETS. However, the Guangdong ETS remains unaffected by short-term channels from other markets. The lagged prices in the Beijing ETS and Hubei ETS have impacts on their current emission allowances prices. Moreover, the Beijing ETS pilot generally led the Shanghai and Shenzhen ETS pilots in a short-run; in other words, the Beijing ETS pilot was the initial receptor of exogenous shocks to its equilibrium relationship and the Shanghai and Shenzhen pilots had to bear the burden of short-run adjustment endogenously in different proportions in order to re-establish equilibrium.

The findings lead to the following considerations: (1) the rank one of cointegration among five jurisdictions is very low and far from achieving a single carbon price in China. The generally low level of co-integration in China's ETS pilots within the sample period may be due to the isolated trading by design, as well as choices of sector coverage and market threshold in each pilot. However, there is a slight indication that the cointegration rank might be two, so there is potential a more robust integration of these markets in the near future. (2) The regional market prices are still dominated by local effects. (3) Liquidity-rich ETS markets, including those with both primary and secondary trading, and a greater presence of foreign and domestic institutional or individual investors, are more likely to have free capital movements, and hence more likely to be co-integrated. (4) The results from this study provide important insights for market participants, especially for institutional and individual investors. In particular, for investors interested in the Shanghai ETS and Shenzhen ETS, using historical information containing the change in Beijing ETS might be a way to improve the short-run forecasting of future carbon prices.

7. Conclusions

Since opening-up of its economy in 1979, China first established four special economic zones to start a market-oriented economic reform, build a pricing system for a market economy with socialist characteristics, and drive the economic development of coastal areas. Since then, China has developed seven special economic zones and succeeded in economic development. Learning from the reform plan of the 1970s, the transition from regional ETSs to a single national ETS fits in with China’s economic and social conditions. The differences among the regional pilot carbon markets becomes a source of gaining insights for improving the market design. Notwithstanding, China's national ETS is in its initial phase, and the trading includes only the power sector. The regional ETS pilots continue to play a vital role since other heavy-emitting industries are currently trading there. At this stage in the construction of a national ETS, this study proposes a number of policy recommendations:

The government should place implementing legislative support for both regional and the national ETS as a priority. It should gradually establish a sound, strict, and unified supervision of trading, and clarify the supervisory responsibilities of authorities and trading institutions at all levels, in order to regulate and manage the regional and national ETS market operations. The absence of supportive legislation for pilots (except for the Shenzhen and Beijing ETSs) or a national ETS would result in a less interest to comply among high-carbon-emitting firms and delays in connecting systems.

With the increasing need to integrate regional carbon markets and limited roles of national ETS in the covering sector at its early phase, linking multiple regional ETS to form a larger 'regional market' has become one of the policy options for further integration. Especially those whose prices enter the long-run relation. The pilots could be linked bilaterally, unilaterally, or indirectly through the common acceptance of some carbon offset standards. This trial would shed a light on linking all regional ETSs to the national ETS.

Finally, the government can consider organizing China's national ETS in trading phases, learning from EU ETS. The first phase is to trial the trading. The second phase tries to include more sectors, for instance, heating, cement, manufacturing, public transport, and domestic aviation, and gradually linking with regional ETSs. The next stage should be a revision-and-reform stage, meaning that the government should consider how to link the domestic ETSs to the international unit to prevent carbon leakage. Given the critical stage of development of the national ETS, greater attention should be paid to developing an appropriate auction mechanism to improve market efficiency for the regional and national ETSs.

It should be noted that there is some further work to do on this topic. For instance, it is possible that the long-run relationship among the variables changes due to regulatory change. Econometric technique such as time-varying cointegration or vector error correction model could be applied when more data are available. In addition, the powerful artificial intelligence models that capture the nonlinear, complicated relationship among regulation rules and the factors regarding ETS can be considered in future research. More broadly, the literature has devoted relatively little attention to the environmental justice aspect of carbon pricing. There has been growing concern over equity aspects versus efficiency considerations.