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Price Dynamics and Interactions between the Chinese and European Carbon Emission Trading Markets

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Abstract: The European carbon emission trading market is the largest and most mature market, while China's carbon market has a short history. Institutionally, cross-market transaction is infeasible between the two markets. This paper investigates the long-run trend between the two markets as well as the price dynamics. Results show that a long-run trend exists between the Chinese and European carbon markets. Both markets possess self-correction capability in reducing price deviations, signaling a certain level of market efficiency. However, both markets also exhibit pricing inefficiency as historical price movements are able to impact prices. The European market informationally leads the Chinese market. Policy implications are that China should further upgrade its information disclosure system, such as unifying information disclosure standards across industries, and further develop its carbon derivatives markets to improve market transparency and market competition.

Keywords: carbon market; long-run trend; price dynamics; European ETS; Chinese ETS

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1. Introduction

Carbon emission trading is one of the most important market-based designs to reduce carbon emissions. Launched on 1 January 2005, the European carbon emission trading market has the longest history and is the largest carbon trading market in the world [1,2]. In comparison, China's carbon emission trading market has quite a short history. The national carbon market was launched on 16 July 2021 after years of regional pilot operation. In view of the fact that China has surpassed the US to be the largest carbon emitter in the world, the carbon emission trading market has never been more important to China's efforts for emission reduction [3]. Whether the carbon market can function well becomes a brightened dot on the radar of policy makers while pricing efficiency is critical to the functioning of carbon market. Specifically, is the carbon market able to self-correct the pricing error and incorporate market innovations into the price? This paper aims to shed some light on this issue by quantitatively investigating the long-run trend between the Chinese and European carbon markets, as well as their price dynamics using the VECM (Vector Error Correction Model) method.

As the largest and most mature market, the European carbon emission trading market has been the research focus. Charles et al. investigate the efficiency of the European carbon market. By checking the EU carbon market in phase II from 2008 to 2012, they examine the cointegration relationship between the futures contracts and spot prices and consider the market inefficiency given the rejection of the cost-of-carry model [4]. However, Montagnoli and de Vries make a different conclusion regarding the market efficiency. They test the efficient market hypothesis using variance ratio tests and report that the European carbon market restores its efficiency in phase II after 2007 [5]. Tang et al. use the VECM method to investigate the pricing efficiency of the European carbon market by looking at futures contracts. They find that the futures contracts for the European carbon market are efficient within one month [6]. Using an agent-based simulation incorporating electricity and carbon markets, Richstein et al. study the effects of backloading of EU emission allowances (EUA) and market stability reserve (MSR) on carbon price and volatility [7]. Crossland et al. consider the EU carbon market not informationally efficient given the robust short-term momentum and medium-term overreaction phenomena [8]. Galan-Valdivieso et al. report that the market regulation mechanisms within the EU after 2013 improve confidence and stability in the EU carbon market [9]. Lee et al. further explore the degree and change of informational efficiency of the EU carbon market. They report that the informational efficiency of the EU carbon market has improved with time and the market efficiency tends to be relatively weak during the upward period [10].

Besides market efficiency, the interaction of the carbon market with other sectors is another research frontier. Ji et al. discover that Brent oil price is able to impact the European carbon emission price while the carbon market can spill over to other energy markets [1]. Zhou et al. investigate multidimensional risk spillover effects by considering together the markets of carbon, energy, and nonferrous metals. Regarding portfolio diversification, they reveal the dynamic risk spillover effects among the markets of carbon, energy, and nonferrous metals. The risk spillover behaviors depend on conditions [11]. Demiralay et al. explore the derivatives of carbon contracts, finding that the carbon futures display benefits of hedging and diversification [12]. Zhou et al. document that the Bitcoin attention Granger causes the carbon futures with a negative impact [13].

Being a market with a short history but huge market potential, China set up several regional pilot markets in succession since 2013, and then the national market started trading in 2021. China's carbon market has been attracting the attention of researchers. Compared to the mature markets, China's carbon market needs to further improve its market liquidity and information transparency based on the performance of its regional pilot markets [14,15]. Regarding market efficiency, Zhao et al. conclude that China's carbon market displays weak form efficiency based on their ADF and run tests on the regional pilot markets [16]. However, more researchers have obtained contradicting results. Research utilizing advanced econometric analyses documents that China's carbon markets are inefficient, given that historical price movements have influences on the carbon emission trading price [17,18]. Wang et al. find that the Chinese regional pilot markets are overall inefficient since five out of six pilot markets follow a mean reversion process [19].

As a financial market, carbon emission trading market's price brings profits and losses to participants in the market. Determinants of the price dynamics further become the research focus. Zhao et al. investigate the price dynamics in China's regional pilot markets using the nonlinear Granger causality technique. They detect bidirectional nonlinear Granger causalities among the pilot markets [20]. Guo and Feng study the spillover effects and report that there are return and volatility spillovers among the pilots. They further show that the price dynamics of individual pilots are driven mainly by their own factors [21]. Li et al. investigate the impacts of various economic policy uncertainties on China's carbon price. They claim that both trade policy uncertainty and monetary policy uncertainty impose positive effects on the carbon price while the exchange rate policy uncertainty comes with a negative influence [22]. Wen et al. report that macroeconomy risk and uncertainty, energy, and environmental factors all possess influencing capacity on the fluctuations of the carbon price fluctuations [23]. Xia et al. document that the carbon market often is the receiver of the risks from the high-carbon-emitting industries [24]. Wang et al. examine whether there is any connection between the European and Chinese carbon markets. They find the existence of a cointegration relationship between the European and the regional pilot market of China [25].

It can be seen from the above literature that although carbon emission markets in China and Europe are the important research objects of academia, there are still some research gaps. Firstly, the existing literature mainly focuses on the study of the individual markets in China or Europe, not covering much of the interaction between the two markets. In particular, there might exist long-run relationships between the two markets. Price movements in one market might informationally lead price movements in the other market. Secondly, most of the research on the Chinese market uses data of the regional pilot market instead of the national market that better reflects the latest situation of the Chinese market. Therefore, it is impossible to make a comprehensive judgment on the development of the Chinese carbon market.

This paper aims to fill the research gaps and shed some light on the ongoing research on the carbon markets. We utilize data of China's national carbon market to assess the overall development of China's carbon market. Institutionally, cross-market transaction is infeasible between the Chinese and European carbon markets. However, as a financial market, the carbon market should reflect the fundamental trend of carbon emission if it functions well. Therefore, whether a cointegration relationship exists between the two markets reveals the level of efficiency of the carbon markets. We apply the cointegration test and VECM to investigate the long-run trend and price dynamics of the Chinese and European carbon markets. It is found that a long-run trend exists between the two carbon markets and the two markets exhibit a certain level of self-correction capability for the short-run price deviations. The European carbon market informationally leads the Chinese market.

The rest of the paper is organized as follows. We introduce the methodology and the data in Section 2. Section 3 conducts a case study analysis for the period with the rapid price rising. Section 4 reports the estimation results and makes a discussion. Lastly, Section 5 concludes the paper.

2. Methodology and Data

2.1. Methodology

Let y_t be the k-vector price of carbon markets. In our case, $k = 2$ since only the Chinese and European carbon markets are involved. p^{CN} and p^{EU} are the corresponding Chinese and European prices, respecitvely. That is, $y_t = \left(p_t^{CN}, p_t^{EU}\right)'$. Usually, price series are nonstationary with I(1) processes. Consider a (q + 1)-order VAR (Vector Autoregression)

$$y_t = A_1 y_{t-1} + \cdots + A_{q+1} y_{t-q-1} + e_t,$$

where A_i is the $k \times k$ coefficient matrix and e_t is a k-vector of white noises. The VAR can be transformed by first differencing and then rewriting into the VECM as below:

$$\Delta y_t = \Pi \cdot y_{t-1} + \sum_{i=1}^{q} \Gamma_i \cdot \Delta y_{t-i} + e_t, \quad (1)$$

where $\Pi = \sum_{i=1}^{q+1} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{q+1} A_j$, I is the identity matrix. Given that y_t is I(1) process, Δy_t is stationary. Whether $\Pi \cdot y_{t-1}$ is stationary or not would impact the regression of VECM, which would be handled by the cointegration test.

According to Johansen (1991, 1995), if Π has reduced rank $r < k$, r measures the number of cointegration relationships [26,27]. Consisting of the relevant I(1) variables, a cointegration relationship specifies the long-run trend to which the variables converge. Besides long-run trends, short-run dynamics might exist. In the short-run, it is possible that price could deviate from the long-run trend. The deviation is named the error term or cointegration term. If markets are efficient, the error term could be corrected gradually by short-run adjustment. The matrix Π can be written in terms of the matrix of adjustment parameters α and the matrix of cointegrating vectors β. That is, $k \times r$ matrices α and β exist such that $\Pi = \alpha\beta'$ and $\beta' y$ satisfies a property that $\beta' y$ is stationary, i.e., I(0). $\beta' y$ forms an r-vector of error terms. The short-run adjustment is captured by the matrix α. With this setting, $\Pi \cdot y_{t-1}$ is stationary so that regression is feasible.

To test the number of cointegration relationships r, Johansen (1995) develops the likelihood ratio (LR) tests based on the coefficient matrix Π. The Johansen cointegration tests utilize the maximum eigenvalue test and the trace test to determine the value of r.

For the maximum eigenvalue test, the null hypothesis is the number of cointegration relationships $r = r_0$ while the alternative hypothesis is $r = r_0 + 1$. The test statistic is

$$LR(r_0, r_0 + 1) = -T \ln\left(1 - \lambda_{r_0+1}\right),$$

where λ_{r_0+1} is the $(r_0 + 1)$th largest eigenvalue.

For the trace test, the null hypothesis is the number of cointegration relationships $r = r_0$ while the alternative hypothesis is $r_0 < r \leq k$. The test statistic is

$$LR(r_0, k) = -T \sum_{i=r_0+1}^{k} \ln(1 - \lambda_i).$$

By comparing the test statistics with the corresponding critical values, the number of cointegration relationships could be determined straightforwardly in practice.

2.2. Data

Inspired by the existing literature, we adopt the EUA (European Union Allowance) spot price of the EEX (European Energy Exchange) and China's national carbon emission trading market spot price to represent the European and Chinese carbon prices, respectively [4,25]. The daily average transaction prices of EU and China are abstracted from a third-party database, Wind. As China's national carbon emission trading market started transactions on 16 July 2021, the sample covered in this research ranges from 16 July 2021 to 30 November 2022, with a total of 365 observations. Note that the trading hours for the EUA are 08:00 to 18:00 (CET), and the transaction date is the same as the Chinese one. Therefore, time-lag adjustment is unnecessary for our current research investigating the lead-lag relationship between European and Chinese carbon emission prices.

The price time series are transformed into the natural logarithm form, the first difference of which is the return or growth rate of carbon prices. r^{EU} and r^{CN} denote the price growth rates of EU and China's carbon allowances, respectively. Table 1 reports the summary statistics for the price growth rates. The averages of r^{CN} and r^{EU} are 0.000 and 0.001, respectively, indicating that there is no apparent monotonic increasing or decreasing trend in China's carbon price, while the European carbon price tends to increase over the sample period. Note that r^{EU} displays larger magnitudes than r^{CN} in terms of maximum, minimum, and standard error. Return on European carbon price tends to be more volatile. In addition, both return time series exhibit fat-tailed distributions with kurtosis much larger than 3. Table 2 reports the correlation between the two returns. Overall, the correlations are very small, with a value of −0.002. It seems the two carbon markets have a very weak connection.

Table 1. Summary statistics.

	r^{CN}	r^{EU}
Average	0.000	0.001
Maximum	0.094	0.274
Minimum	−0.067	−0.286
Standard dev.	0.018	0.038
Skewness	0.773	−0.743
Kurtosis	10.381	22.159
Jarque-Bera	862.534 ***	5600.601 ***

Notes: *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Table 2. Pairwise correlation.

	r^{CN}	r^{EU}
r^{CN}	1.000	
r^{EU}	−0.002	1.000

Checking the unit root properties of all the time series, we find that both natural logarithmic forms of price time series are I(1) processes with their returns I(0). Upon the I(1) properties of price time series, we conduct a cointegration test to investigate any cointegration relationship between the prices using the technique of Johansen (1991, 1995). As reported in Table 3, both the trace statistic and maximum eigenvalue statistic indicate that there is one long-run relationship between the two prices. As shown in the sequel, deviation from the long-run relationship is denoted by CointEq1.

Table 3. Johansen cointegration test.

r	Trace Statistic	5% Critical Values	Max-Eigen Statistic	5% Critical Values
$r \leq 0$	21.792 **	20.262	19.766 **	15.892
$r \leq 1$	2.026	9.165	2.026	9.165

Tests of the existence of long-run relationships among the prices. r is the number of cointegration relationships. ** denotes significance at a level of 5%.

3. Case Study Analysis

Figure 1 plots the price and price growth rate of the Chinese and European carbon markets over the sample. Since the beginning of 2022, the price of the Chinese market has been stable at a high level, while the price of the European market has fluctuated to some extent, but it is also stable on the whole. At the same time, we particularly noted that the European market experienced a rapid rise from November 2021 to February 2022, with the price rising from 57.71 to 97.48 Euro/metric ton CO_2. That is, the European ETS (emission trading system) price increased by almost 70% within just three months. A similar rapid rise also occurred in the Chinese market, but with some lag. From December 2021 to January 2022, China's carbon emission trading price rose from 41.46 to 61.38 RMB/metric ton CO_2, a nearly 50% increment in two months. It seems that the Chinese and European carbon prices have some certain connection. At least they might share some common trend.

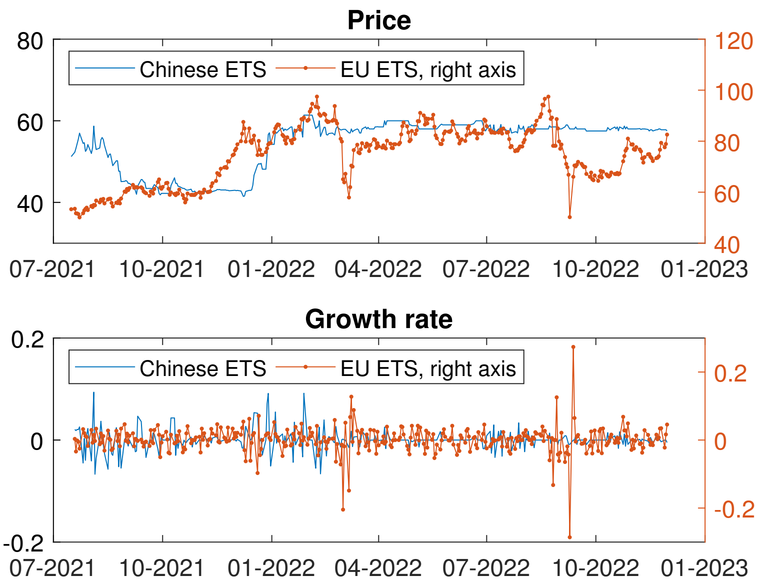

Figure 1. Prices and price growth rates of the Chinese ETS (emission trading system) and EU ETS. Note that the price units for the Chinese and EU ETS are RMB and Euro, respectively.

From the perspective of price growth rate, there are several extreme values in the price growth rate of the European market. In contrast, the price growth rate in the Chinese market is relatively stable, and the number as well as the magnitude of the extreme values are smaller than those in Europe. Nevertheless, there are some similarities between the two markets. During the period from the end of 2021 to the beginning of 2022 when prices of both markets rapidly increased, both markets exhibited the phenomenon of volatility clustering. From the price growth rate of the two markets, it again shows that the two markets might be related.

Regarding the elevated carbon price of European ETS from the end of 2021 to the beginning of 2022, some politicians blame financial speculators, believing that these financial speculators should be excluded from the market. However, data analysis shows that the open market position held by financial speculation did not change too much. At the same time, the existence of financial speculation can reduce the overheated price by releasing the position. Therefore, financial speculation should not be the main driving factor. On the contrary, economic and political factors should be the main driving forces. In 2021, the price of natural gas relative to coal in the global market rose sharply, causing power generators to turn to coal for power generation. As coal has a larger carbon emission than natural gas, power generators' demand for carbon emission rights increases consequently. At the same time, the climate ambition of European countries is also a key factor. On 14 July 2021, the European Commission proposed a package plan to address climate change, aiming at reducing the net emissions of greenhouse gases in the EU. A key measure of the proposal is to tighten the carbon emissions trading system, which means a reduction in the supply of carbon emission rights. The reduction of supply would certainly cause prices to rise [28].

For the rapidly rising Chinese carbon price at the end of 2021, political will for climate goal is also an important factor. On 27 October 2021, the Chinese government issued the white paper "China's Policies and Actions to Combat Climate Change". China was determined to put climate change in a more prominent position in national governance and continuously reduce the intensity of carbon emissions. With the Ministry of Ecology and Environment further promoting the carbon emission contracts, the national carbon market became more active.

In reality, the two carbon emission markets in China and Europe are not interlinked. However, both markets are faced with climate change objectives and political will, which makes the two markets have a common underlying fundamental. Therefore, the two markets are related in political fundamentals. As for the specific degree of relevance, it needs to be further revealed from a quantitative perspective in a sequel.

4. Results and Discussion

4.1. Results

For the specification of the VECM model, information criterion SIC favors the optimal lag order q to be 1 while AIC favors 5. At lag order 1, it is found that the regression suffers from severe serial correlation. Therefore, we set the optimal lag order q as 5 with one cointegration relationship between p^{CN} and p^{EU}. Table 4 reports the VECM estimation result. The existence of one cointegration relationship indicates the long-run trend between the two carbon prices. According to this long-run trend, the Chinese carbon price tends to co-move with the European carbon price, although cross-transaction is not allowed under the current institutional design. In terms of short-run deviations from the long-run trend, error-correction is observed in both prices by taking into account coefficients in the cointegrating equation and of the error correction term. For example, if either the Chinese or European carbon price deviates from the long-run trend, the deviations would be reduced immediately on the next transaction day, given the significant coefficients of CointEq1_{t-1}.

Regarding short-term price dynamics, effects of the lagged growth rate of prices are detected in the individual carbon market. The growth rate of the Chinese price faces significant and negative effects from its two- and three-period lagged growth rates. The negative effects of the lagged growth rates of price contribute to the phenomenon of mean-reversion, where increases in price tend to be followed by decreases so that no monotonic trend can dominate the price movements. The mean-reversion phenomenon is also found in the European market with r_{t-1}^{EU} and r_{t-5}^{EU} imposing negative effects on r_t^{EU}. Besides the mean-reversion, the European market also exhibits momentum behavior, with the coefficient for r_{t-3}^{EU} significantly positive.

Table 4. VECM estimation result.

	Cointegrating Equation	
Variables	**CointEq1**	
p^{CN}	1	
p^{EU}	−1.265 ***	
	(0.220)	
c	1.457	
	Error Correction	
	r^{CN}	r^{EU}
CointEq1$_{t-1}$	−0.023 ***	0.031 **
	(0.006)	(0.013)
r_{t-1}^{CN}	−0.075	−0.110
	(0.052)	(0.111)
r_{t-2}^{CN}	−0.183 ***	−0.011
	(0.052)	(0.111)
r_{t-3}^{CN}	−0.090 *	−0.045
	(0.053)	(0.111)
r_{t-4}^{CN}	0.046	0.056
	(0.052)	(0.110)
r_{t-5}^{CN}	−0.063	0.036
	(0.052)	(0.109)
r_{t-1}^{EU}	−0.009	−0.094 *
	(0.025)	(0.053)
r_{t-2}^{EU}	−0.009	−0.009
	(0.025)	(0.054)
r_{t-3}^{EU}	−0.050 **	0.122 **
	(0.025)	(0.053)
r_{t-4}^{EU}	−0.004	0.022
	(0.026)	(0.054)
r_{t-5}^{EU}	−0.018	−0.134 **
	(0.025)	(0.053)
c	0.000	0.001
	(0.001)	(0.002)
Log likelihood	1629.978	
AIC	−8.936	
SIC	−8.655	
LM1	0.281	
LM4	0.234	
LM8	0.830	
LM12	0.363	

Notes: standard error in parentheses; *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. LM1, LM4, LM8, and LM12 are the *p*-values for the residual serial correlation LM tests at lag order 1, 4, 8, and 12, respectively.

Market interaction is another potential source contributing to the short-term price dynamics. None of the Chinese market variables have a significant effect on the European price. In contrast, the historical movement in the European market has a significant effect on the Chinese carbon price, with r_{t-3}^{EU} imposing a negative effect on r_t^{CN}.

An important point in regression analysis is serial correlation since serial correlation leads to bias in estimation and inference. As reported in Table 4, our estimation passes the serial correlation tests at various lag orders using the LM test. The residual portmanteau tests for autocorrelation also confirm that our regression is not suffering from serial correlation, which is reported in the paper to save space. Therefore, our estimation is eased from the concern for serial correlation.

To visualize the short-term price dynamics and interaction between the Chinese and European carbon emission markets, we perform an impulse response analysis. Figure 2 displays the impulse responses of dependent variables r^{CN} or r^{EU} to one standard shock in either r_t^{CN} or r_t^{EU}. Both r^{CN} and r^{EU} respond strongly to their corresponding own shocks. Regarding price spillover effect between the two markets, a unidirectional impact from the European market to the Chinese market is observed. A shock in r_t^{EU} would significantly impact r^{CN} in four periods, r_{t+4}^{CN}. In contrast, a shock in r_t^{CN} does not significantly impact the future r^{EU}.

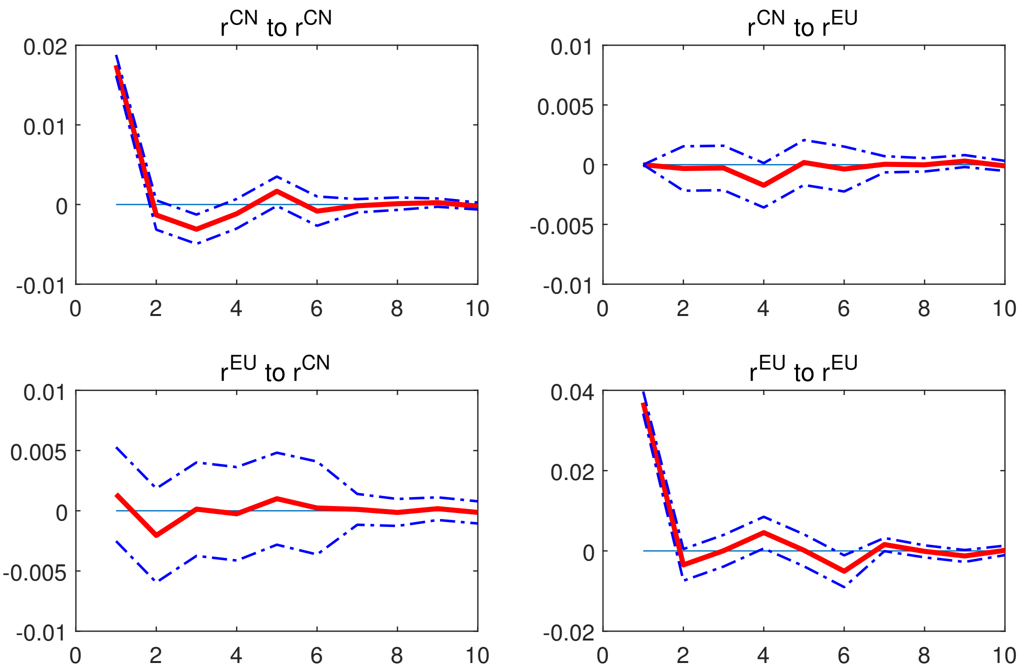

Figure 2. Impulse responses to a standard shock in a two-standard-error confidence band.

As a robustness check, we adopt another cointegration test, the dynamic Engle–Granger two-step approach [29], to perform regression again. The first step indicates that there is one cointegration relationship between the Chinese and European carbon markets. In the second step with the error correction regression, the estimation result reported in Table 5 is consistent with our baseline result reported in Table 4. That is, both markets possess self-correction capability in reducing short-term price deviation. Historical movements in price impact pricing in the two markets. In addition, there is a unidirectional influence from the European market to the Chinese one. Our empirical analysis result is robust to different econometric techniques.

Table 5. VECM estimation result using the dynamic Engle–Granger two-step approach.

	Long-Run Equation	
	p^{CN}	
p_{t-1}^{CN}	0.978 ***	
	(0.009)	
p_t^{EU}	0.006	
	(0.025)	
p_{t-1}^{EU}	0.011	
	(0.025)	
c	0.017	
	Error Correction	
	r^{CN}	r^{EU}
CointEq1$_{t-1}$	−0.030 ***	0.034 **
	(0.008)	(0.016)
r_{t-1}^{CN}	−0.069	−0.119
	(0.052)	(0.111)
r_{t-2}^{CN}	−0.178 ***	−0.020
	(0.052)	(0.111)
r_{t-3}^{CN}	−0.086	−0.053
	(0.052)	(0.111)
r_{t-4}^{CN}	0.049	0.049
	(0.052)	(0.110)
r_{t-5}^{CN}	−0.060	0.031
	(0.052)	(0.109)
r_{t-1}^{EU}	−0.009	−0.097 *
	(0.025)	(0.053)
r_{t-2}^{EU}	−0.010	−0.011
	(0.025)	(0.054)
r_{t-3}^{EU}	−0.050 **	0.119 **
	(0.025)	(0.054)
r_{t-4}^{EU}	−0.005	0.018
	(0.026)	(0.054)
r_{t-5}^{EU}	−0.018	−0.136 **
	(0.025)	(0.054)
c	−0.196 ***	0.220 **
	(0.050)	(0.106)
Log likelihood	1629.222	
AIC	−8.943	
SIC	−8.683	
LM1	0.258	
LM4	0.239	
LM8	0.792	
LM12	0.324	

Notes: standard error in parentheses; *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively. LM1, LM4, LM8, and LM12 are the p-values for the residual serial correlation LM tests at lag order 1, 4, 8, and 12, respectively.

4.2. Discussion

Our finding of one long-run trend between the Chinese and European carbon market is consistent with the result of Wang et al. who investigate the cointegration relationship using the regional pilot markets of China [25]. They document the existence of cointegration between the Beijing pilot market and the European market without further checking the relationships between European market and other pilot markets of China. For a nation with heterogeneous development stages, like China, a regional pilot market might not be able to represent the national market well. Utilizing the latest data of the recently launched national carbon market of China, we contribute to the literature by documenting the cointegration relationship between the European market and the Chinese national market. The finding that both markets possess self-correction capability in reducing price deviations implies market efficiency to some extent.

Regarding short-term price dynamics, we reveal the impacts of historical prices in both markets, which is consistent with the results of existing literature [17,18,23]. Compared to the Chinese carbon market, the European carbon market is subject to more influences from the historical price movements. The impacts of the historical price movements suggest that both Chinese and European carbon markets do not satisfy the weak form efficiency in which the historical data of a market should not affect the market price.

From the perspective of the lead–lag relationship, the market interaction between the Chinese and European carbon markets indicates the informationally leading position of the European carbon market, consistent with the status of the European carbon market as the most mature and well-developed market. As an emerging market, the Chinese carbon market informationally follows the European market even though the two markets are not connected institutionally. Zhao et al. claim that the Chinese carbon market is not as efficient as the European one given the lack of good transparency [30]. Sun et al. investigate the volatility of the two markets and conclude that the Chinese market is relatively inefficient compared to the European one [2]. In line with the literature regarding the status of the Chinese carbon being less mature, we complement the finding from the perspective of the price lead–lag relationship.

5. Conclusions

Set up in 2005, the European carbon market is the world's first international emissions trading system. Sixteen years later, on 16 July 2021, China launched its national carbon emission trading market. Given the context that the market design does not allow cross-market transactions, are the two markets effectively isolated? Would the Chinese market reflect the trend of the international carbon market? This paper quantitatively investigates the long-run relationship as well as the market interaction between the two markets.

After verifying the nonstationary property of the price time series, we find one cointegration relationship between the Chinese and European carbon prices. The two prices tend to co-move in the long run. In the short run, it is possible to have price deviations from the long-run trend, which reveals the market efficiency of the two carbon markets. Concerning the short-run price deviations, the two markets are able to self-correct the price deviation by gradually reducing the magnitude of price deviations so that individual prices would converge to the long-run trend. The self-correction for the short-run price deviations signals certain market efficiency in both markets.

Regarding price dynamics, both markets are subject to the influences of historical price movements, exhibiting mean-reversion patterns so that continual monotonic movements in prices are rare. Besides mean-reversion, the European market also faces a positive impact from its historical price movements. Further checking market interactions, it is found that there is a unidirectional spillover from the European market to the Chinese one. The European market informationally leads the Chinese market while the Chinese market could not incorporate the international market innovation into its price immediately. The impacts of historical data on the Chinese and European carbon prices imply that both markets so far have not met the requirement of weak-form market efficiency.

From the result for the lead–lag relationship between the Chinese and European carbon markets, we are able to offer some policy implications. The Chinese carbon market should further improve its information disclosure system. At present, China has not established a complete and unified carbon information disclosure framework. Different industries have different standards, and too many information disclosure standards lead to information disclosure confusion. At the same time, companies face challenges in the cost and technology of information disclosure. In view of the role of derivatives markets in improving market mechanisms, China should further develop its carbon derivatives markets, such as futures and options markets, to improve market transparency and competition.

Compared to traditional financial markets, such as the stock and foreign exchange markets, the carbon emission trading market is still immature, especially for the Chinese carbon market. The theme of this paper is the efficiency of the carbon market. One of the limitations of the current research is the lack of exploration of the factors influencing market efficiency. Directions for future research could further investigate the market efficiency. How should the market efficiency of the carbon market be quantified? What are the determinants of the market efficiency of the carbon market? Addressing these questions should improve the market design and operation of the carbon market.

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