Factors Affecting China's Carbon Trading Price—A Case Study Based on Tianjin Carbon Emissions Trading Market

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Abstract

Building a carbon emission trading market is an effective way to control carbon emissions. The carbon emission trading price is the key to the carbon trading market, and it will affect the carbon emission reduction behavior of enterprises. This study use the vector autoregression (VAR) model, the cointegration analysis, and the Granger causality test to analyze the influence of industrial development index (Shanghai Stock Exchange Industrial Index (000004.SH)), coal price index (National Coal Price Index), air quality index (AQI), and economic index (Purchasing Managers Index (PMI)) on the carbon emission trading price in Tianjin. Empirical research results based on data from January 2014 to December 2019 show that the Shanghai Stock Exchange Industrial Index and AQI are positively correlated with Tianjin carbon emission trading price, and the National Coal Price Index and PMI are negatively correlated with Tianjin carbon emission trading price. Finally, some suggestions are made to promote the rapid maturity of the national carbon emission trading market of China.

1. Introduction

Over half a century, the rapid growth of industrialization has dramatically increased fossil fuel consumptions and greenhouse gas (GHG) emissions (Smil, 2017), which is a threat to the global environment (Zheng et al., 2015; Guo and Liang, 2016). Carbon dioxide (CO₂) emission is one of the main factors behind high environmental pollution, and its reduction is globally discussed (Calel and Dechezleprêtre, 2016; Wu et al., 2020). In this regards, in 1997, based on the United Nations Framework Convention on Climate Change, the international community passed the 'Kyoto Protocol' that came in to effect in 2005 and then the global economies have established carbon emission trading markets. Later rapid expansion in the scale of carbon trading and turnover observed. A survey conducted by Refinitiv (2020) showed that the global carbon market transaction volume in 2019 has exceeded 230 billion US dollars. Since China joined the World Trade Organization (WTO) in 2001, rapid urbanization and industrialization cause high CO₂ emissions (Peters et al., 2020). As the US and China are the highest energy consumers and GHG emitters, they need energy conservation and GHG emissions reduction. In this regards, China's energy conservation and CO₂ reduction actions are of great significance to a sustainable environment (Yang et al., 2018; Zhou and Li, 2019). As a staunch supporter of the 'Kyoto Protocol,' the Chinese government has clearly stated specific tasks for building a carbon trading market in the "Twelfth Five-Year Plan" to reduce carbon reduction. In 2013, Shenzhen established China's first carbon exchange and then Beijing, Tianjin, Shanghai, Guangdong, Hubei, Chongqing, and Fujian have consecutively been approved to establish carbon emission trading pilot markets. Since 2013, a series of CO₂ reduction measures such as establishing carbon emissions trading pilots have greatly slowed China's carbon emissions (Peters et al., 2020). In 2015, the Chinese government set an ambitious goal at the 11th United Nations Climate Change Conference, that is, by 2030, not only the carbon emissions peak will be reached, but also the CO₂ emissions per unit of GDP will be reduced by 60-65% from the 2005 level (Li et al., 2018a). In 2020, during the 75th UN General Assembly, the Chinese government proposed to increase its nationally determined contributions, to adopt more effective policies and measures, and

strive to achieve carbon neutrality by 2060 (Mallapaty, 2020). To accomplish these couple of goals, China faces enormous pressure to reduce its CO₂ emissions.

The establishment of a carbon trading system is one of the effective means to control carbon emissions. Since 2013, China has accumulated a lot of valuable experience through running carbon emissions trading pilots, and a single carbon emissions trading market is more efficient for reducing carbon emissions (Fan et al., 2016). Therefore, China proposed to build an unified national carbon emissions trading market before the end of 2020 in the "13th Five-Year Plan". In 2020, China started a nationwide emission transaction system (ETS), but currently it only covers coal and gas-fired power plants (IEA, 2020), and there is still a long way to go and achieve nationwide carbon emission trading. To simulate China's national carbon emissions trading market's maturity, it is necessary to recognize China's carbon emissions trading problems. The most important thing about ETS is its carbon emission trading price.

China's carbon emission trading market is still young, and there is a lack of consensus on factors that affect the carbon emission trading price in the existing literature. Previous studies were mainly focused on the carbon trading markets of Hubei, Shenzhen, Beijing and Shanghai (Zhou and Li et al., 2019; Hao and Tian, 2020; Zeng et al., 2017; Lyu et al., 2020; Jia et al., 2018). At present, there is still a lack of research on the factors affecting carbon emission trading price in the Tianjin carbon trading market. Among the eight pilot cities for carbon emissions trading in China, Tianjin is the only carbon emission trading pilot city that has participated in both low-carbon provinces and regions, low-carbon cities, greenhouse gas emission inventory compilation, and regional carbon emissions trading pilots. At the same time, Tianjin Carbon Emissions Exchange is China's first comprehensive environmental energy trading platform. The Tianjin carbon trading market is mainly based on carbon allowance trading, supplemented by China Certified Emission Reduction (CCER), and the allocation method of allowances is mainly "free allocation + auction" (Gong, 2019). However, unlike other pilot areas, the CCER of the Tianjin Carbon Exchange has restrictions in terms of geography, project types, emission boundaries, etc. (Gong, 2019; Liao et al., 2019). In addition, the Tianjin Carbon Emissions Trading Market is the first carbon trading market to realize the convergence of accounting methodology with China's national standards. Therefore, studying the influencing factors of the carbon emissions trading price in the Tianjin carbon trading market is of great significance for promoting the maturity of the national unified carbon emissions trading system. Thus, this study will fill this gap and also contribute to the existing literature.

The rest of the paper arranged in the following manners: section 2 comprised on the relevant literature review; section 3 included on the research methods and data definition; section 4 cover the results and discussion of the study; section 5 composed on conclusions and policy recommendations.

2. Literature Review

2.1. Industrial development:

Alberola et al. (2008a) surveyed 9 EU countries, and they found that both fuel and steel industries have significant impacts on carbon prices. China is a rich industrialized country, and industrial development is in the transition stage towards a green environment. Industrial development causes high carbon emissions and affects carbon prices fluctuation (Du and Liu, 2018). Yang et al. (2018) believe that frequent industrial activities will generate a large amount of CO₂ emissions, which will lead to a shortage of carbon allowances and increase the price of carbon emissions trading. Ma and Zhao (2016) used principal component analysis to study voluntary emission reduction transactions in China's carbon emissions trading and found that the level of industrial development is negatively correlated with the average transaction price of carbon emissions trading in Beijing. (Ji et al., 2021) found that industrial activities generate extensive CO₂ emissions, and when carbon allowances are too sufficient, then the price of carbon trading rights will fall. However, a small number of studies took the Shanghai Industrial Index (000004.SH) into consideration and found mixed and blended results. Therefore, the inconclusive results call for further studies to investigate and present the exact correlation between industrial development and carbon price in this region.

2.2. The Carbon Price Index:

A small number of prior studies deliver that energy prices have little effect on carbon trading prices (Zhao and Hu, 2016). Other empirical works show that the price of carbon emissions trading can significantly affect energy prices. For instance, Hintermann (2010) originate that coal prices harm the price of carbon allowances in the EU ETS market. Keppler and Mansanet-Bataller (2010) confirm that the carbon futures prices in EU ETS (2005-2007) were affected by coal and natural gas prices. Kim et al. (2010) deliberate the impact of energy prices on the US market for carbon allowances, and they found that long-term carbon allowance trading has a significant effect on coal prices. Some scholars verified that the coal price fluctuations have the most significant impact on carbon prices through recurrence plot (RP) and recurrence quantification analysis (RQA) methods, followed by natural gas, and crude oil price fluctuations have the least impact on carbon price fluctuations (Wu et al., 2020). Hammoudeh et al. (2014) probed the impact of coal on the price distribution of carbon emission allowances in the US and found that coal prices would negatively affect carbon prices. Besides, Li and Lei (2018) found that energy prices mainly affect carbon trading prices. For example, traditional energy prices are correlated positively with the average Beijing carbon emission trading price. (Zeng et al., 2017).

2.3. The Air Quality Index (AQI):

The carbon emissions trading market is a climate-sensitive market, and fluctuations in air quality will lead to fluctuating energy demand, which will impact the price of trading in carbon. Zhou and Xu (2016) developed a vector error correction model to analyse the carbon price in the Shenzhen trading market. They found that coal prices and AQI have the greatest impact on domestic carbon emissions' trading price. Li et al. (2018b) found that as air quality policies become more stringent, carbon prices will rise

accordingly. Yin et al. (2019) studied China's carbon trading market and found a negative correlation between Beijing's AQI and carbon trading prices. Han et al. (2019) conducted an empirical study on the Shenzhen carbon market through the Mixed data sampling (MIDAS) model analysis of the AQI. The results showed that AQI is one of the essential factors affecting the carbon trading price. Zhou and Li et al. (2019) researched the Hubei carbon trading market found there is a long-term balance between the price of chromium for carbon emissions and the quality of the air.

2.4. The economic factors:

Economic development significantly impacts the fluctuation of carbon emission rights trading prices (Xu et al., 2019). Aatola et al. (2013) propose that the demand for carbon emissions and carbon allowances will also rise when the economy is booming. Koch et al. (2014) investigated whether the decline in European Emission Allowances (EUA) prices from mid-2008 to mid-2013 was caused by the economic recession and found that economic activity can reflect EUA prices. Alberola et al. (2008b) found that whether industrial production on EUA prices was positive or negative depended on the economic status. From a macroeconomic perspective, structural economic transformation is conducive to companies to reduce emission reduction costs, thereby ensuring a stable carbon trading price (Springer et al., 2019). The international macroeconomic situation has a greater impact on the EU's ETS development expectations and the carbon price fluctuations in the carbon emission rights market. For example, the last plunge in international oil prices caused the future settlement price of the EUA market to drop sharply in December 2015, and it was not until February the following year. There are signs of rebound (Sun et al., 2020).

In a nutshell, the above literature shows a lack of consensus on the research on Tianjin Carbon Emissions Trading Price factors. In addition, this study will enrich the existing literature on the influencing factors of China's carbon emissions trading price, which is still worth discussing.

3. Research Methods And Data Definition

The current literature on the influencing factors of carbon emissions trading prices mainly focus on the following aspects:

3.1 Research methods

This study adopted the Vector Autoregressive Model (VAR), a commonly used technique to study the mutual influence of economic variables. Based on this model, this study analyzes in detail, through impulse response, the impact of each influencing factor on China's carbon allowance price. The VAR model constructs a model that is based on the data's statistical properties. To construct the model, it takes every endogenous variable in the system as a function of the lag value of all endogenous variables. It extends the univariate autoregressive model to a variable of a multivariate time series. The VAR model

here contains four endogenous variables namely; industrial development index, coal price, air quality, and economy. The mathematical equation of the theoretical VAR model as under:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + B x_t + \varepsilon_t \quad t = 1, 2, \dots, T \quad (1)$$

where, where y_t is the k -dimensional endogenous variable column vector, x_t is the d -dimensional exogenous variable column vector, p is the lag order, and T is the number of samples. The $k \times k$ -dimensional matrix $A_1, \dots, A_p$ and $k \times d$ -dimensional matrices B are coefficient matrices to be estimated, and ε_t is a k -dimensional perturbation column vector. Each element is non-self-correlated, but allows correlation between different elements. The selection of the lag order of the VAR model mainly includes LR (likelihood ratio), AIC (Akaike) statistical method, and SC (Schwarz) criterion. And adopt a co-integration test to judge whether there is a long-term equilibrium relationship between Tianjin carbon emission trading price and driving factors directly.

We respectively indicate that the industrial development index, carbon price index, air quality index, and economic index are INDUSTRIAL, COAL, AQI, and PMI. We expect a positive correlation between the Tianjin carbon emission trading price and the industrial development index, and the economy. The trading price of emission rights has a negative correlation with coal prices and air quality. We conduct an empirical analysis to prove our hypothesis.

$$P_{Carbon} = F(INDUSTRIAL, COAL, AQI, PMI) \quad (2)$$

3.2 Variable selection and data sources

The Tianjin Climate Exchange was officially opened in Tianjin on December 26, 2013, and included industries such as steel, chemical, electric power and heating, petrochemical, and oil and gas mining. In this study, we selected the average daily carbon transaction price announced by the Tianjin carbon emissions trading platform from January 2014 to December 2019, and the unit is yuan/t. The monthly average price obtained after the arithmetic average processing is used as the explained variable, and there are 72 samples in total. Based on the existing research literature and the Tianjin carbon emissions trading market's actual situation, the demand factors that affect the price of Tianjin carbon emission trading were selected as explanatory variables.

3.2.1 Industrial development level

The Shanghai Stock Exchange Industry Index (000004.SH), which reflects China's industrial development speed, is selected as an indicator to reflect the level of industrial development. This is because the carbon

emissions in industrial sectors are much larger than other industries, and it is the industrial sector that usually needs to purchase carbon emission permits. As macroeconomic and industrial levels develop, both the industrial sector's carbon emissions and carbon emission trading demand will increase. Hence, the industrial index was selected as an indicator that affects the price of carbon emission rights.

3.2.2 Carbon Energy Price

China's carbon emissions is mainly derived from coal consumption, which resulted in a natural price transfer mechanism between the fossil fuel market and the carbon market. The rise in energy prices will boost the rise in carbon market prices, while the decrease in energy prices will also drive the reduction in carbon market prices. Many scholars have supported and verified this transmission path.

3.2.3 Air quality Index

The AQI of Tianjin is selected as the air quality indicator. This is because of the increase in air pollution simulated China's carbon emission trading development in recent years. A direct hand of carbon emissions is the level of air pollution, i.e. the increase in industrial emissions, greenhouse gases, and CO₂ emissions is to some extent reflected in air quality. Therefore, Tianjin's air quality index, where the Tianjin Emissions Trading Center is located, is selected as the air quality indicator.

3.2.4 Economic activity

Carbon emission trading is significantly affected by economic activities. The supply-demand relationship of allowances is determined directly by economic activities. Economic activities increase, market trading activity is high, allowance demand increases, and carbon market prices rise; conversely, economic activity decreases, market trading activity is low, allowance demand decreases, and carbon emission trading price fall. Many scholars have verified and supported this transmission path. This article selects the monthly manufacturing Purchasing Managers Index (PMI) published by the Tianjin Bureau of Statistics to measure economic activity.

This article selects Tianjin's carbon emission allowance price as the dependent variable, and China Industrial Development Index, coal price, AQI, and economic level as independent variables. The data sources are shown in Table 1.

4. Results And Discussion

4.1 Descriptive statistical analysis of data

The data used in this article are from January 2014 to December 2019. We used the average of each month to fill in the missing data, thus obtaining 72 time series data points. Fig. 1 shows the trend graph

of the transaction price of Tianjin carbon emissions trading. Before December 2015, because the Tianjin carbon emissions trading market was in the early stage of development and the rules and regulations were not perfect, the price of carbon trading often fluctuated sharply (Gong, 2019). Most of the carbon allowances in the Tianjin carbon trading market belong to large enterprises (especially power companies). Therefore, carbon trading prices are susceptible to fluctuations due to the performance period of the enterprises. In addition, the Tianjin carbon trading pilot market is dominated by allowance trading, supplemented by CCER trading. The quota trading is mainly concentrated around June each year to complete the transaction and fulfill the contract, while CCER only began to enter the carbon trading market in early 2015, and is subject to various restrictions such as regional restrictions, time restrictions, and technical type restrictions, and is often suspended by exchanges. , Resulting in extremely fragmented CCER trading prices, so the early Tianjin carbon emissions trading prices often fluctuate sharply. At the same time, the Tianjin carbon trading market is mainly based on the primary market and lacks price linkage with the secondary market. The government rather than the market plays a leading role in the Tianjin carbon trading market. Therefore, in different periods, carbon trading prices in the Tianjin market are quite different. After December 2015, the Tianjin carbon emissions trading market has developed more and more perfect in all aspects. Therefore, except for the three periods from May 2016 to September 2016, July 2017 to August 2017, and April 2018 to June 2018, the carbon trading prices in other periods are relatively stable.

The descriptive statistical results of each time series are shown in Table 2. The null hypothesis of the normal distribution is strongly rejected by all-time series through the Jarque-Bera test.

4.2 Test of the model establishment

This paper uses a co-integration test to determine whether there is a long-term equilibrium relationship between carbon market prices and driving factors. First of all, to guarantee the VAR model is effective and avoid the phenomenon of 'false regression', we first perform unit root tests on the research problem's relevant data to test its stationarity. As displayed in Table 3, to test the stationarity of all the variables to be studied, the unit root method is used (Carbon, AQI, Industrial, PMI, Coal). The test results show that the sequence is stationary after the first-order difference. When building the VAR model, we use the first-order difference sequence. Therefore, a multiple linear regression model of carbon emission trading price, Industrial, AQI, coal, and PMI can be introduced. The multiple linear regression model is shown below:

$$Carbon = \beta_0 + \beta_1 Industrial_t + \beta_2 Coal_t + \beta_3 AQI_t + \beta_4 PMI_t + \varepsilon_t \quad (3)$$

where t represents the month t of the research period and ε is the error term.

The Johansen cointegration technique is used to determine whether it is possible to consider the above multiple linear regression model as a long-term balance relationship. The test results are shown in Table

4. The findings show that the price of the carbon market and different driving factors reject the null hypothesis that there is no co-integration relationship at the 5% significance level. The results of the Granger causality test are shown in Table 5. The results revealed that the price of Tianjin carbon emission trading price was not only significantly affected by coal prices, but also by air quality and industrial development status.

In building the VAR model, we focus on selecting the variables with strong correlation and the final lag order to reflect the variables' influence. Through the above test, it can be understood that each variable has a certain degree of stability. As shown in Table 6, combine the test results of SC, LR, FPE, AIC, and HQ and choose the column's lag order with most asterisks. If the two columns have the same number of asterisks, then select the lag order with the smaller AIC, then the VAR model's optimal lag period can be selected as 1.

Fig. 2 demonstrates the results of the VAR model's AR root test consisting of five variables. The AR root test indicates that the unit circle contains all the characteristic roots, demonstrating that the model has good stability. A VAR model with five variables is therefore established, and the overall model fit is good.

4.3. Impulse response analysis

A variable's impact affects its modifications and affects other related variables, using the VAR model's dynamic structure as a medium. After taking AR roots for testing, the reciprocal of all root moduli of the estimated VAR model was less than 1 (we're located in the unit circle), which indicated that it is stable and verified the validity of the results. This article sets the response time length to 50 days based on VAR stability and analyses the impulse response function with a 95 percent confidence interval, and the results are shown in Fig. 3. In the tiny graph in Fig. 3, the horizontal axis represents the impact action period of hysteresis, and the vertical axis represents the degree of the impulse response. The solid line represents the function of the impulse response which is the response of the price of the Tianjin carbon allowance to its price, Shanghai Stock Exchange Industrial Index, Coal Price Index, AQI, and PMI, and the dotted line represents the deviation band of the positive response and the negative response.

Based on the Tianjin carbon emission trading price's impulse response, it can be seen that the price of carbon emission trading is most affected by itself and PMI. The Shanghai Stock Exchange Industrial Index and AQI have the second-highest impact, and the coal price has the least impact on Tianjin carbon emission trading price. Among them, the Shanghai Stock Exchange Industrial Index and PMI harm the Tianjin carbon emission trading price, and the coal price and AQI have a positive impact on Tianjin carbon emission trading price. As shown in Fig. 3a, the pluse of Tianjin carbon emission trading price had the greatest impact on itself in the current period. It was gradually weakened and reached an equilibrium state in the 43rd period, indicating that Tianjin carbon emission trading price is more sensitive to its impact. The results in Fig. 3b demonstrated that a standard deviation of the Shanghai Stock Exchange Industrial Index will cause carbon emission trading price to fall within 3 days and gradually increase from the 3rd day to the 27th day, reaching equilibrium on 27 days, with a change rate of 0. This shows that

industrial development fluctuations will be transmitted to the price of carbon emission trading in Tianjin within a relatively short period. Still, the impact will become smaller and smaller as time goes by, until it disappears. It can be seen from Fig. 3c that a change in the standard deviation of the coal price will cause a slight increase in Tianjin carbon emission trading price, a slight increase in the first three days, a decrease from the third day, and a return to the initial price on the seventh day. It remains unchanged thereafter. This shows that the impact of coal prices on the Tianjin carbon emission trading price is very small and short-lived and can be ignored. As depicted in Fig. 3d, the impact of a standard deviation of air quality will cause a short-term decline in Tianjin carbon emission trading price within one day, with a decrease of 0.15% and then a sharp rise reaching the maximum on the fourth day. The increase was 0.4%, and then began to decline, and fell to 0 within 30 days and remained unchanged. This shows that the Tianjin carbon emission trading price responds very quickly to changes in air quality. Fig. 3e demonstrate the response of the Tianjin carbon emission trading price on the impact of PMI changes. The carbon emission trading price declined rapidly when it was impacted by the change in PMI and continued to decrease from the 2nd to the 9th day. It gradually increased after the 9th day and returned to the initial value on about the 42nd day, indicating that economic fluctuations will immediately be transmitted to the Tianjin carbon emission trading price and have a long-lasting impact on the carbon trading price.

4.4. Variance decomposition

This study examines the influencing factors of the trading price of carbon emissions in Tianjin, so this study only carry out variance decomposition analysis on the Tianjin carbon emission trading price. Based on the analysis of variance decomposition, we explained how each variable affects Tianjin carbon emission trading. We can determine the contribution of each structural impact on endogenous variables by analysing variance decomposition, and then we can evaluate the importance of various structural impacts.

From the results of variance decomposition (Table 7), we can see that with the gradual decrease of variance contribution, the contribution rate of Tianjin carbon emission trading price to its price changes is declining, but the price of Tianjin carbon emission trading is mainly affected by its historical price. In addition to the Tianjin carbon emission trading price itself, the impact of industrial development has contributed the most to changes in Tianjin carbon emission trading price, followed by economic, air, and carbon price impacts. The variance decomposition results are greater than and stabilized since the seventh period.

5. Conclusions And Policy Recommendations

This study aims to research on influencing factors of Tianjin Carbon Emissions Trading Price from January 2014 to December 2019. In this study, industrial development index, carbon price, AQI, and PMI were selected as explanatory variables, their influence on Tianjin carbon emission trading price was

evaluated using econometric methods such as cointegration analysis and Granger causality test. The results show that the industrial development index and AQI are positively correlated with Tianjin carbon emission trading price; contrarily, the carbon price index is negatively correlated with Tianjin carbon emission trading price. Whereas, the economic PMI index has no obvious influence on the price of Tianjin carbon emission trading. CO₂ emissions from industrial production account for a larger share of the total CO₂ emissions, which will lead to more demand for carbon emission trading. As a result, the industrial development index and AQI are positively correlated with the carbon emission trading price. With the increase in clean energy such as natural gas, rising coal prices will decline the demand for carbon emission trading. The oversupply of carbon emission trading in the market has led to a decline in carbon emission trading price, which makes Tianjin's carbon price and the price of carbon emission trading negatively correlated. Economic activities affect the development of the carbon emission trading market. Still, current attention of the Tianjin carbon emission trading market is on the industry, and the Tianjin carbon emission trading market's construction is in the preliminary stage. Hence, the price of carbon emissions trading is relatively small.

The Tianjin carbon trading pilot started relatively late. Given the number of companies participating in the carbon market and the completeness of the carbon market's legal system, there is a large gap between the carbon market and other markets that trade in carbon emissions. As one of China's carbon emissions trading markets, its operational experience plays a key role in building a single national carbon emissions trading market.

There is a certain gap between Tianjin's carbon emission measurement standards and other carbon markets. Tianjin has fewer tertiary industries. Under the existing measurement standards, fewer companies include carbon emissions reductions, which seriously restricts the growth of Tianjin's carbon trading market. The Tianjin carbon trading market's carbon emission measurement problem is mainly because the national carbon trading market has just been established and lacks complete laws and regulations and national carbon emission accounting standards. One is that the form of punishment is single or even lacking. Tianjin has not announced corresponding measures such as direct penalties for non-performance. Other provinces and cities, such as Guangdong and Hubei, provide for fines and the payment of quotas. That is to say, if a company conducts excessive carbon emissions, it will not only need to pay a fine but also be compulsory to pay the carbon allowance to offset the excess of zero emissions. The legal liability is relatively heavy, making it unprofitable if the company fails to perform. Second, other constraints lack rigidity or even become formalism. Tianjin only stipulates that it cannot enjoy the flexible measures of financing support and financial support preferential policies within 3 years. Compared with other provinces and cities, including blacklist management, including enterprise credit records and exposure, they are not rigid and deterrent. We should strengthen the supervision of laws and regulations and implement strict total control.

The Tianjin carbon trading market is mainly relying on the primary market. It lacks price linkage with the secondary market, and especially for some small energy-consuming companies, these companies' carbon emissions are not included in the total carbon emissions. The market does not play a leading role

in the economic activities of carbon trading. For the Tianjin carbon trading financial market, how to formulate and implement the market standard system is the driving force for Tianjin carbon emission enterprises to reduce emissions.

The construction of the market for trading carbon emissions is inseparable from the cultivation and development of talent, which is the driving force behind the market's growth for trading carbon emissions. Talents in this field in Tianjin are slightly insufficient in terms of professional knowledge and capabilities. At present, Tianjin urgently needs professionals in the fields of carbon finance and carbon accounting. It is necessary to actively cultivate relevant talents and relevant institutions, further improve relevant systems, create a more complete platform, strive to be in line with international standards, and be consistent with international standards. Therefore, it is essential to increase the talent pool, cultivate third-party forces, and actively independent research and development.

The above are the Tianjin carbon emissions trading market problems, and they are also should be paid attention to in the comprehensive promotion of the carbon emissions trading market. To absorb Tianjin's pilot project's experience to build a national carbon market, the most important thing is to strengthen carbon emission sources' supervision. Carbon emission rights trading is a market behavior under the supervision of national institutions. Therefore, we must first strengthen the management of emission rights by relevant departments; secondly, The development of environmental monitoring facilities by internationally required standards will seriously damage China's carbon trading market's healthy development. China's regional economic development level, energy consumption status, and natural environment vary greatly. Therefore, the allocation of allowances should reflect regional differences, taking into account the industrial distribution in the eastern, central, and western regions, as well as the ability of different industries to reduce carbon emissions. Simultaneously, the regional carbon price of China is heavily influenced by macroeconomic and industrial growth. Government departments should establish a corresponding quota buffer mechanism based on actual economic conditions to control the total amount of quotas.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

Yuwei Du: Conceptualization, Methodology, Investigation, Writing - Original Draft preparation, Data analysis; Songsheng Chen: Conceptualization, Funding acquisition, Supervision, Review.

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Tables

Table 1

Explanatory variables and data sources.

Variable	Metrics	Data sources
Carbon price	Tianjin carbon emissions trading price	Tianjin Carbon Emissions Trading Platform
Industrial Development Index	Shanghai Stock Exchange Industrial Index (000004.SH)	Wind
Coal price	National Coal Price Index	Wind
Air quality	Air quality index (AQI)	Air quality online monitoring and analysis platform
Economy	Purchasing Managers Index (PMI)	National Bureau of Statistics

Table 2

Descriptive statistics results

	CARBON	INDUSTRIAL	COAL	AQI	PMI
Mean	17.42	2400.12	611.06	104.68	50.6
Median	14.59	2402.92	622.50	100.00	50.3
Maximum	37.50	3883.78	842.16	175.00	52.4
Minimum	8.51	1670.36	489.00	72.00	49.7
Std. Dev.	7.26	404.05	104.55	23.07	0.76
Skewness	0.76	0.88	0.63	0.85	0.46
Kurtosis	2.80	5.61	2.42	3.16	1.85
Jarque-Bera	6.97	29.73	5.75	8.78	6.49
Probability	0.03	0.00	0.06	0.01	0.04

Table 3

Stationarity test result.

Variable	Model	5%	t-Statistics	P-value	Result
CARBON	NCNT	-1.945	-1.182	0.215	Non-stationary
INDUSTRIAL	NCNT	-1.946	-0.159	0.625	Non-stationary
COAL	NCNT	-1.946	-0.007	0.677	Non-stationary
AQI	NCNT	-1.945	-1.221	0.202	Non-stationary
PMI	NCNT	-1.945	-0.123	0.638	Non-stationary
DCARBON	CNT	-2.904	-8.236	0	Stationary
DINDUSTRIAL	CNT	-2.904	-5.768	0	Stationary
DCOAL	CNT	-2.906	-8.275	0	Stationary
DAQI	CNT	-2.904	-8.591	0	Stationary
DPMI	CNT	-2.904	-9.516	0	Stationary
CT: constant and trend, CNT: constant and no trend, NCNT: no constant and no trend					

Table 4

Cointegration test result.

Null hypothesis	Trace statistic value	P value
No	309.509	0.000
Up to 1	181.191	0.000
Up to 2	100.785	0.000
Up to 3	18.707	0.016
Up to 4	3.305	0.069

Table 5

Granger causality test results.

Variable	Carbon	Industrial	Coal	AQI	PMI
Carbon	-	0.475	0.887	0.212	0.941
Industrial	0.072*	-	0.901	0.693	0.890
Coal	0.009***	0.638	-	0.712	0.475
AQI	0.054*	0.562	0.348	-	0.020
PMI	0.520	0.985	0.032	0.996	-
Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels (two-sided).					

Table 6

Criteria information for VAR model.

VAR Lag Order Selection Criteria						
Exogenous variables: C						
Included observations: 64						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1400.503	NA	8.18E+12	43.922	44.091	43.988
1	-1226.755	314.918*	7.85e+10*	39.274	40.286*	39.672*
2	-1205.671	34.921	9.01E+10	39.396	41.251	40.127
3	-1191.841	20.745	1.32E+11	39.745	42.444	40.808
4	-1172.238	26.341	1.69E+11	39.914	43.456	41.309
5	-1143.584	34.027	1.70E+11	39.800	44.185	41.527
6	-1119.425	24.914	2.12E+11	39.826	45.054	41.886
7	-1080.493	34.066	1.84E+11	39.390	45.462	41.782
8	-1050.785	21.352	2.49E+11	39.243*	46.158	41.968
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Table 7

The variance decomposition of the influencing factors of carbon price.

Variance Decomposition of DCARBON:						
Period	S.E.	DCARBON	DINDUSTRIAL	DCOAL	DAQI	DPMI
1	2.924	100	0	0	0	0
2	4.011	96.152	2.434	0.040	0.127	1.247
3	4.754	92.583	5.226	0.073	0.703	1.415
4	5.358	90.190	6.614	0.101	1.332	1.762
5	5.817	88.844	7.335	0.136	1.564	2.121
6	6.154	88.001	7.854	0.142	1.607	2.397
7	6.407	87.354	8.271	0.157	1.605	2.613
8	6.601	86.848	8.568	0.179	1.601	2.804
9	6.752	86.464	8.760	0.196	1.595	2.984
10	6.868	86.168	8.883	0.209	1.586	3.154
11	6.960	85.933	8.959	0.220	1.577	3.311
12	7.031	85.742	9.003	0.230	1.569	3.456
13	7.088	85.585	9.027	0.237	1.561	3.590
14	7.132	85.454	9.036	0.244	1.554	3.712
15	7.168	85.343	9.037	0.249	1.547	3.824
16	7.196	85.249	9.032	0.253	1.542	3.925
17	7.219	85.167	9.024	0.257	1.537	4.016
18	7.237	85.097	9.014	0.259	1.533	4.098
19	7.252	85.035	9.004	0.262	1.529	4.170
20	7.264	84.982	8.994	0.264	1.526	4.235
21	7.274	84.935	8.984	0.266	1.523	4.292
22	7.282	84.894	8.975	0.267	1.521	4.343
23	7.288	84.858	8.967	0.268	1.519	4.387
24	7.293	84.827	8.960	0.269	1.517	4.426
25	7.298	84.800	8.953	0.270	1.516	4.461
26	7.301	84.776	8.947	0.271	1.514	4.491
27	7.304	84.755	8.942	0.272	1.513	4.517

28	7.307	84.737	8.938	0.272	1.513	4.540
29	7.309	84.722	8.934	0.272	1.512	4.560
30	7.310	84.708	8.931	0.273	1.511	4.577
31	7.312	84.696	8.928	0.273	1.511	4.592
32	7.313	84.686	8.926	0.273	1.510	4.605
33	7.314	84.677	8.923	0.274	1.510	4.606
34	7.315	84.669	8.922	0.274	1.510	4.625
35	7.315	84.662	8.920	0.274	1.509	4.634
36	7.316	84.657	8.919	0.274	1.509	4.641
37	7.316	84.651	8.918	0.274	1.509	4.647
38	7.317	84.647	8.917	0.274	1.509	4.652
39	7.317	84.644	8.916	0.274	1.509	4.657
40	7.317	84.640	8.916	0.274	1.509	4.661
41	7.318	84.638	8.915	0.274	1.508	4.664
42	7.318	84.635	8.915	0.275	1.508	4.667
43	7.318	84.633	8.914	0.275	1.508	4.669
44	7.318	84.632	8.914	0.275	1.508	4.671
45	7.318	84.630	8.913	0.275	1.508	4.673
46	7.318	84.629	8.913	0.275	1.508	4.675
47	7.318	84.628	8.913	0.275	1.508	4.676
48	7.318	84.627	8.913	0.275	1.508	4.677
49	7.318	84.626	8.913	0.275	1.508	4.678
50	7.318	84.625	8.913	0.275	1.508	4.679

Figures

Figure 1

Transaction price of Tianjin Carbon Emissions Trading.

Inverse Roots of AR Characteristic Polynomial

Figure 2

Stationarity test of VAR model.

Figure 3

The results of impulse responses of Tianjin carbon emission trading prices.