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What Factors Influence the Price of Carbon Emission Trading in China? A Case of Beijing Carbon Market

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Abstract: As an efficient measure to deal with the intensification of the greenhouse effect, markets for carbon emission trading have been considered to establish by governments in developed countries. However, A stable price system has not yet developed for China's carbon trading market, which is still in its early stages. Therefore, to stabilize the price of carbon trading, enhance the carbon trading price system, and support the wholesome growth of the carbon trading market in China, it is essential to conduct research on the factors that affect carbon trading price. Based on the trading mechanism and the monthly data of the Beijing carbon trading market from 2014 to 2020, this paper investigates the influence patterns of energy price, industrial development, macroeconomic growth, and air quality on carbon price changes, and unit root test, Johansen cointegration test, and error correction model are used to analyze the patterns. The empirical results show that industrial development, economic growth, energy prices, and air quality have a long-run equilibrium relationship with carbon prices. While industrial development indicators are negatively correlated with the price of carbon, the price of energy, economic growth, and air quality are positively correlated with the price of carbon emission trading. Finally, some relevant development suggestions are proposed according to the empirical results.

Keywords: carbon credits, carbon price, influencing factors

1. Introduction

In recent years, the global economy has been growing rapidly, and economic growth has led to increasingly serious environmental problems. Excessive carbon emissions have led to the greenhouse effect, which is responsible for the frequent harsh weather. Countries all over the world have reached a consensus to develop a low-carbon economy and protect the atmosphere, and have begun to cooperate to explore the path of climate governance. By the end of June 2016, nearly 180 countries had signed the Paris Climate Change Agreement and reached a consensus on strictly controlling global temperature rise. And then the "carbon trading" mechanism was created. “Carbon trading” refers to the commodification of carbon emission rights and their circulation in the market, thus creating an efficient mechanism to reduce carbon emissions. In addition, the creation of carbon credits as a commodity effectively reduces the negative externalities caused by the reckless emission of carbon dioxide by enterprises.

As the second-biggest carbon emitter in the world and the largest developing country, China has always made environmental protection and sustainable development a key development concept, and in 2011, the Development and Reform Commission designated two provinces and five cities for the initial trial of carbon trading. On July 16, 2021, the National Carbon Emissions Trading Market was established. In March this year, President Xi emphasized that China should achieve "peak carbon by 2030 and carbon neutrality by 2060", and included it as an important evaluation criterion in the government work report for the first time. Therefore, it is important to establish a sound and efficient carbon trading market and form a stable carbon trading price mechanism to achieve these two goals.

The carbon trading market in China is still in its infancy at present. Policy measures, market mechanisms and other aspects are not yet perfect, and prices have not formed a perfect and stable price system. The key to the construction of the national carbon emissions trading market is the development of carbon price mechanism, and a good price mechanism would encourage the market for carbon to grow healthily. But what factors influence the price of carbon trading in China? But what factors affect China's carbon trading price? How to stabilize the trading price of carbon rights? How to promote the development of China's carbon trading market?

Therefore, a more comprehensive analysis of China's carbon trading market prices and its influencing factors is important for establishing a perfect price system in the domestic market, fighting for pricing power, stabilizing price fluctuations in the carbon market, and promoting long-term development of the domestic market. In recent years, most scholars have studied China's carbon trading market price formation mechanism and its influencing factors analysis, and they have established single-factor model or multi-factor model from the perspective of oil prices, macroeconomic development, etc. This paper is based on the mechanism of carbon emissions trading, considering the supply and demand side of the carbon trading market and its related influencing factors on the impact of carbon trading prices, and takes Beijing carbon trading market as an example. The monthly carbon price data from 2014 to 2020 are used as the explanatory variables, and the data of related influencing factors are selected as the explanatory variables. Unit root test, Johansen cointegration test, and error correction model are used. The empirical analysis of the data is conducted to verify the relationship between energy prices, industrial sector development, macroeconomic growth, and climate. The equilibrium relationships between energy prices, industrial sector development, macroeconomic growth, climate factors, and carbon trading market prices are verified, and corresponding empirical conclusions and relevant suggestions are drawn. This study may offer pertinent references for enhancing China's carbon emission trading market's pricing system and also theoretical references for advancing the creation of a national unified carbon emission trading market.

2. Literature Review

The EU carbon emission market was established earlier and developed relatively maturely, studies on the influencing elements of carbon trading prices and studies on the influencing factors of EUA futures prices are the two primary areas of studies on the relatively mature EU carbon trading system. Among the studies on the influencing elements of carbon prices, FANY et al. established a copula model and found that the effect of regulatory policies that have a significant impact on the demand and supply of EUA will be more significant in influencing carbon allowance prices[1]. Zhang C et al. founded the price of carbon is positively connected with economic development, which is higher when the economy is booming and lower when the economy is in recession [2]. In the study of EUA futures price, foreign scholars Grunwald et al. had a conclusion that electricity price and coal price have a positive influence on EUA futures price, and macroeconomic factors also have a big impact on the price, while the influence of crude oil price is not significant [3]. Rebored concluded that there is a strong mean-dependent and extreme symmetric association between EUA prices and crude oil prices using a time-varying copula model to conclude that there is a positive mean-dependent and extreme symmetric relationship between EUA prices and crude oil prices [4].

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There are two types of studies on the variables that affect the carbon trading price market in China: the influence of a single factor on carbon trading price, and multifactor analysis. Among the studies on single factors, regarding the influence of energy prices, Qi et al. and Zhao and Wei came to the opposite conclusion: Qi et al. found that the price of carbon trading and the energy price are positively correlated linearly. while Wei who used panel data by generalized least squares concluded there is a negative correlation[5,6]. Regarding the influence of policy factors, Li and Chen determined whether environmental protection policies have a significant influence on China's carbon trading price by testing the statistical significance of cumulative abnormal returns [7]. By constructing a propensity score matching double difference (PSM-DID) model, Wang and Wang Ziyao analyzed the significant impact of carbon emissions trading pilot policies on carbon emission reduction and economic development in pilot provinces and cities in China [8]. Regarding the influence of macroeconomic factors, Zhang et al. used a panel data model [9], and Zhou used the VAR model to find that economic activities have the most influence on carbon trading prices among many other reasons [10]. In the study of the influence of multiple factors on carbon trading price, scholars used principal component analysis and GA-BP neural network model to study the relationship between energy, economy, climate, and other multiple factors and carbon prices. And reached a consistent conclusion: Ma and Zhao discovered a positive correlation between the average transaction price of BEA and economic development, while a negative correlation existed between the price of traditional energy and the average transaction price of BEA [11]. Du and Liu concluded that natural gas prices and exchange rates significantly increase the price of carbon trading [12].

From the above researches, the direction and magnitude of the influence derived from them varies depending on the period of their variable selection and the carbon market pilot, as can be seen from the fact that many academics have developed various models in recent years to analyze the influences of carbon trading pricing from various perspectives. From the research methods on carbon emission trading prices, No scholars used the error correction model. By considering how the supply and demand sides of the carbon trading market determine prices, this paper studies the long-run and short-run equilibrium relationship between the factors influencing carbon trading price and carbon price by using the Johnson cointegration test and error correction model.

3. Analysis of the influencing factors of carbon emission trading price

3.1. Supply-side

The supply side of the carbon trading market is divided into two main areas. On the one hand, is the government, and the supply from the government side is the main influencing factor in the market supply. The carbon trading system is founded on the right to use finite resources, and to ensure that resources are allocated as efficiently as possible, the government first distributes carbon emission allowances by the finite total emissions. On the other side, the market's quota excess businesses. The government first distributes carbon emission allowances by the total amount of emissions that are allowed, but some businesses have different demands for carbon emission allowances on the market, such as businesses that have excess carbon emission demand and businesses that have excess emissions. If an enterprise has surplus allowances, it can sell them; if the enterprise's emissions exceed the allowances, it can buy the allowances in the market. This trading system is a market-oriented environmental policy tool that encourages enterprises to achieve emission reduction tasks at the lowest cost according to their emission reduction costs and market signals.

So supply side factors are allowance policies, including the number of allowances, allocation methods, interperiod reserve systems, etc.

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3.2. Demand-side

The demand side mostly consists of carbon trading market emission control businesses that must make carbon emissions. Enterprises will compare their marginal abatement cost size with the carbon market price. If their own abatement cost is higher than the carbon price, then enterprises choose to buy allowances and they will bear the loss of reduction. If the opposite is true, the enterprise will sell the allowances or store them for the next period, making a profit or anticipating future profits.

Macroeconomic development, industrial development, energy prices, environmental changes, and other demand-side factors have an extremely important impact on the price fluctuations of quota trading.

3.2.1. Macroeconomic development.

Since the world entered the industrial revolution, economic development has been rapid, and at the same time, carbon dioxide emissions have been increasing. Some scholars have confirmed through empirical studies that there is an environmental Kuznets curve between CO2 emissions and economic, i.e., environmental quality typically deteriorates initially before improving as a result of economic growth [13]. while the current structure and stage of China's economic growth show that the urbanization makes industry develop continuously in the future, and economic growth leads to the environmental deterioration [14].

Macroeconomic development is related to the product development of enterprises. According to the theory of supply and demand, When the country's economic development trend is good, enterprises will expand their production, and output value will rise, with this, resource consumption will rise, driving up demand for carbon emissions and the cost of carbon trading; when the economic development is low, enterprises will reduce the scale of production, the price of carbon trading will decline as the demand for carbon emissions declines. Therefore, the movement of carbon trading price is positively correlated with the macroeconomic development dynamics.

3.2.2. Industrial Development.

Carbon emissions mainly come from industrial sectors, different stages of industrial development will affect the fluctuation of carbon prices. The demand for carbon emissions and the price of carbon trading will change as a result of the diverse ways that businesses use energy at different stages of their development. In the primary stage of industrial development, the priority and importance of industrial development are mentioned before environmental protection, and environmental protection is neglected; in the mature stage of industrial development, the public begin to pay attention to the importance of environmental sustainability, and the government will try to reduce the negative externalities of economic development by technological progress and innovation. Although the energy demand will not decrease, there will be a change in the energy structure and a greater demand for clean energy, which will modify how carbon emission rights are demanded.

3.2.3. Energy prices.

Fossil energy generates large amounts of carbon dioxide gas. Therefore, when carrying out production, fluctuations in energy prices lead to changes in the energy demand, companies consequently changes in CO2 emissions, which ultimately affect the number of carbon credits demanded by companies and the price of carbon credits.

On the one hand, the fluctuation of energy prices will make companies control and adjust their production costs. On the other hand, energy rising costs will encourage businesses to adopt new technologies, alter their energy consumption patterns, and boost energy efficiency, which will reduce carbon dioxide emissions. Finally, as the demand for carbon emissions declines, the price of carbon trading also changes.

3.2.4. Environmental factors.

On the one hand, the emergence of severe weather will attract the attention of the government and other relevant departments, and for the protection of the environment, the government will promulgate a series of policies and propose restrictions on the use of energy etc. The demand for carbon emission rights will rise, which will drive up the price of carbon emission trading; On the other hand, when extreme weather occurs, the relevant departments will control the price of carbon to force enterprises to adjust the structuring of energy utilization and increase energy use efficiency. As a result, there will be less demand for carbon credits, which will have an impact on their price.

Through the theoretical analysis of carbon trading price formation, it can be seen that carbon trading price is influenced by two sides, among the supply-side factors of carbon trading price formation, the guiding role of quota policy and carbon emission reduction technology factors is a long-term influence process. while in the demand-side factors part, macroeconomic development, industrial development, energy prices, and environmental changes have an impact on the formation of carbon trading prices in China.

4. Model construction

4.1. Variable selection and data sources

According to the analysis of the price formation, the supply and demand sides of the economy are both able to affect the price of carbon rights. Among them, the supply side is mainly determined by the government, but the decision of government quotas and the influence of policies are relatively stable factors, on the other hand, the data of supply-side variables indicating policies are difficult to obtain and measure, based on which it is determined in the theoretical model to study only the influence of demand-side factors.

The following indicators were selected based on the existing literature on the influence factors of carbon credits and the availability of data, as shown in Table1.

Table 1: Selection of variables and data sources.

Type	Variables	Variable Symbols	Definition	Data source
Explained variables	Carbon trading price	P	Carbon trading price in Beijing pilot market	China Carbon Emissions Trading Network
Explanatory variables	Energy Price	E	Bohai Sea Power Coal Price Index	China Coal Trading Network
	Industrial Development	I	SSE Industrial Index (closing price)	www.investing.com
	Macroeconomic Development	G	CSI 300 Index (Closing Price)	www.investing.com
	Environmental Factors Indicators	A	Air Quality Index AQI	www. aqistudy.cn/
		CO	CO emissions	www.aqistudy.cn/

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4.1.1. Price of carbon credits

The carbon emissions trading price in this paper is selected from the monthly average carbon trading price in the Beijing carbon emissions trading market from 2014 to 2020. The Beijing Carbon Emissions Exchange was officially opened on November 28, 2013, at the Beijing Environmental Exchange, covering more than 500 enterprises in the large construction industry, manufacturing industry, and power generation. Since the market's launch, its volume and turnover have topped the other seven carbon trading pilots.

4.1.2. Energy Price Indicators

In terms of the selection of energy price indicators, foreign scholars usually choose oil and natural gas as energy price indicators. However, it is found that coal makes up the majority of China's entire energy usage, and since the overall energy production in China is affected by the epidemic in 2020, raw coal accounts for 69.3% of all energy sources from the composition of total energy production in 2019, so coal price is chosen as the explanatory variable, see Figure 5-1. to China coal trading network in the Bohai Sea Power coal price index to show the trend of energy prices, and to match the sample size of carbon trading prices, the weekly data of Bohai Rim power coal prices are monthly averaged to obtain the price index from January 2014 to December 2020.

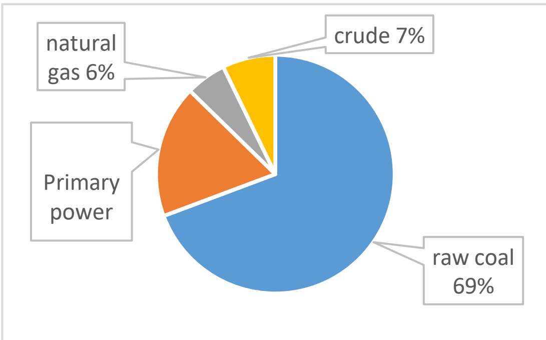

Figure 1: Composition of China's total energy production in 2019.

4.1.3. Industrial Development Indicators.

In terms of the selection of indicators to express the development of the industrial industry, there are mainly three indices, SZSI, CSI Industrial Index, and SSE Industrial Index, and the three indices are weighted to express the development trend of the whole industrial industry by selecting the share prices of representative industrial industry enterprises. Since the data of SZSE Industrial Index is only counted up to 2015, CSI Industrial Index is only counted up to 2016, and only SSE Industrial Index meets the date price required in this paper, the monthly closing prices of CSI 300 Index from 2014 to 2020 are selected to show the development of the industrial industry. The industry weight distribution of the CSI 300 index reaches 45.46% in financial real estate. Therefore the CSI 300 index largely represents the development of the financial industry.

4.1.4. Macroeconomic Development Indicators

In terms of macroeconomic development indicators, concerning scholars such as Guo and Zhou take the CSI 300 index as a representative indicator of economic development [15,16]. When used as a basis for evaluating investment performance, the CSI 300 index responds to the compilation goals and operational status of the CSI 300 index jointly announced by the Shanghai and Shenzhen Stock

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Exchanges on April 8, 2005. In the sense that it can provide a reference standard for indexed investment, the CSI 300 index can reflect the development of macroeconomic conditions. Therefore, this paper selects the CSI 300 index from January 2014 to December 2020 as an indicator to show macroeconomic development.

4.1.5. Environmental Factors Indicators

In the selection of environmental factor indicators, the monthly air quality index (AQI) of Beijing from 2014 to 2020 was chosen to show the change in air quality. It is because AQI describes the degree of clean or polluted air, and as a comprehensive index AQI can visually reflect the air pollution status. larger AQI values indicate worse air quality. On the other hand, considering that the emission of carbon dioxide when enterprises perform fossil energy combustion also brings the emission of carbon monoxide gas, the change of carbon monoxide content in the air is added to the environmental factor index.

4.2. Model selection

4.2.1. Pre-regression analysis.

Regression analysis can show the correlation between the variables, and improve the effectiveness of the prediction equation. According to the theoretical analysis in Part III to determine energy prices, industrial development, macroeconomic, and environmental factors will have an effect on the carbon trading price. The following model is created based on research and analysis of the factors influencing carbon prices.

$$LNP_t = \beta_0 + \beta_1 LNE_t + \beta_2 LNI_t + \beta_3 LNG_t + \beta_4 LNA_t + \beta_5 LNCO_t + \varepsilon_t \tag{1}$$

In equation (1), the β_0 is the constant term, the β_i is the coefficient term, and ε_t is the random perturbation term.

4.2.2. Johnson co-integration test.

Because the data selected is the time series data from 2014-2020, when building the time series model if the regression of non-stationary time series will lead to pseudo-regression, so the test of ADF stationarity is necessary. In addition, if the variables are correlated with each other, it will affect the explanatory ability of explanatory variables to the explained variables, so to avoid the occurrence of multicollinearity, the correlation of variables should also be tested. After the smoothness test, Considering the information loss of the regression analysis using the differenced series, the Johansen test was chosen to avoid the "pseudo regression" to show the relationship between the variables.

4.2.3. Error correction model.

Although the cointegration test can show whether the linear combination of nonstationary time series has a stable equilibrium relationship, deviations from equilibrium may occur in the short run. so it is necessary to establish an error correction model to further test the long-term equilibrium relationship between the variables. If the variables are first-order differential smooth series, the following error correction model can be established.

$$\Delta LNP_t = \beta_1 \Delta LNE_t + \gamma_1 \Delta LNI_t + \delta_1 \Delta LNG_t + \varepsilon_1 \Delta LNA_t + \epsilon_1 \Delta LNCO_t - \lambda ecm + \mu_t \tag{2}$$

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5. Empirical analysis

5.1. Unit root test

The test of smoothness is performed and the results are shown in Table 2

Table 2: ADF test results.

Sequence		0 steps t-test statistic	P-value		Step 1 t-test statistic	P-value
LNP_t	ADF	0.557664	0.8347	ADF	-12.80684	0.0000
	5%level	-1.944811	--	5%level	-1.944811	--
LNE_t	ADF	0.246624	0.7553	ADF	-5.621997	0.0000
	5%level	-1.944862	--	5%level	-1.944862	--
LNI_t	ADF	-2.834104	0.1897	ADF	-6.682211	0.0000
	5%level	-3.465548	--	5%level	-1.944811	--
LNG_t	ADF	-2.186812	0.4903	ADF	-7.221709	0.0000
	5%level	-3.464865	--	5%level	-1.944811	--
LNA_t	ADF	-0.97665	0.2916	ADF	-8.522358	0.0000
	5%level	-1.944969	--	5%level	-1.944915	--
$LNCO_t$	ADF	-0.596996	0.4559	ADF	-10.72117	0.0000
	5%level	-1.944762	--	5%level	-1.944811	--

From Table 2, we can see that the unit root test results of the ADF values are all greater than the critical value at the 5% level, and the original hypothesis cannot be rejected, indicating that the series has a unit root and is nonstationary.

And it can be seen in after the first order difference that all the sequences of ADF values are smaller than the critical values at the 5% level, so the original hypothesis is rejected, indicating that after one difference the series does not have unit roots and is smooth. All the series are first-order single integer series I(1).

5.2. Correlation test of variables

Multiple covariance was tested between the variables and the results are shown in Table 3.
As can be seen in Table 3, the values of each variable in centered VIF are less than 10, indicating that there is no multicollinearity among the selected variables.

Table 3: Multicollinearity test.

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	1.492278	5938.872	--
LNE	0.013705	2145.916	1.423348
LNI	0.072281	17431.95	7.365946
LNG	0.056586	14996.18	9.241742
LNA	0.009153	770.2738	2.517008
LNCO	0.004885	375.6657	2.40289

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5.3. Johansen cointegration test

Table 4 indicates the results of the characteristic root trace test derived. The results in the table demonstrate that there are six cointegration relationships between the variables, and the cointegration test results indicate that the effect of each explanatory variable on the carbon price is stable. And the number cointegration equation is as follows.

$$LNP_t = 1.415010 \times LNE_t - 6.649311 \times LNI_t + 5.960761 \times LNG_t + 0.038155 \times LNA_t - 0.922709 \times LNCO_t + u_t \tag{3}$$

The results show that in the long run, the industrial development indicator and the energy price indicator have the greatest impact on the carbon price.

Table 4: Johansen cointegration test results between variables in eviews

Original hypothesis	Eigenvalue	Trace statistic test			Maximum Eigenvalue Test		
		Trace statistics	5%	P-value	Maximum	5%	P-
None*	0.492	157.682	95.754	0.000	52.797	40.078	0.001
At most 1*	0.368	104.885	69.819	0.000	35.824	33.877	0.029
At most 2*	0.290	69.061	47.856	0.000	26.766	27.584	0.063
At most 3*	0.272	42.295	29.797	0.001	24.720	21.132	0.015
At most 4*	0.135	17.575	15.495	0.024	11.354	14.265	0.137
At most 5*	0.077	6.221	3.841	0.013	6.221	3.841	0.013

5.4. Vector error correction model

The variables show cointegration between variables in the Johansen cointegration test, but deviations from equilibrium may occur in the short run. And the short-run imbalance is normal. In order to study the relationship between long-run equilibrium and short-run adjustment among variables, the following error correction model is established.

$$y = \begin{pmatrix} -1.323729 \\ 0.461135 \\ -1.76399 \\ 0.268854 \\ -0.042073 \\ -0.046963 \end{pmatrix} vecm_{t-1} +$$

$$\begin{pmatrix} -0.168526 & -0.284977 & 1.455728 & -0.258604 & 0.272969 & 0.239654 \\ 0.052465 & 1.184329 & 0.396100 & -0.001392 & -0.197914 & -0.123145 \\ -0.364208 & -0.185181 & 0.986110 & -0.017301 & 0.050353 & 0.082733 \\ 0.053717 & -0.437979 & -2.0887 & 0.244570 & 0.249915 & 0.002513 \\ -0.595001 & -1.801183 & -4.806812 & 0.383266 & -1.809614 & -2.197358 \\ 1.345614 & 2.604273 & 6.205149 & -0.349762 & 1.625171 & 2.069246 \end{pmatrix} \Delta y_{t-1} +$$

$$\begin{pmatrix} -0.4821 & -0.369124 & 0.926464 & 0.196771 & 0.325791 & 0.348677 \\ 0.130524 & 0.680220 & 0.104434 & -0.006552 & -0.26467 & -0.187122 \\ -0.403644 & -0.124747 & 0.758994 & -0.012095 & 0.169272 & 0.166349 \\ 0.705558 & 1.268838 & -0.196092 & -0.369737 & 0.086208 & -0.049851 \\ -0.526656 & -1.169347 & -4.238434 & 0.447265 & -1.299997 & -1.754106 \\ 0.718198 & 1.461078 & 5.132506 & -0.339859 & 1.025316 & 1.559732 \end{pmatrix} \Delta y_{t-2} +$$

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$$\begin{pmatrix} -0.181055 & 0.133554 & 0.640883 & -0.125241 & 0.161756 & 0.163209 \\ 0.088640 & 0.023014 & -0.35016 & -0.014831 & -0.197378 & -0.132181 \\ -0.284546 & 0.235900 & 0.622115 & 0.011515 & 0.158278 & 0.157982 \\ 0.737637 & 0.023911 & -1.079654 & 0.049256 & -0.096893 & -0.236334 \\ -0.633376 & -1.13479 & -2.173231 & 0.241581 & -0.865474 & -1.211451 \\ 1.045380 & 1.844845 & 3.087195 & -0.217654 & 0.590508 & 0.896947 \end{pmatrix} \Delta y_{t-3} + \begin{pmatrix} -0.076739 & 0.283222 & 0.602655 & -0.070655 & -0.017246 & 0.028489 \\ 0.021217 & -0.09199 & -0.158425 & 0.004783 & -0.137619 & -0.103505 \\ -0.098649 & 0.132772 & 0.214611 & 0.002768 & 0.059034 & 0.067751 \\ 0.767539 & 0.872708 & 0.056070 & -0.24236 & -0.036569 & -0.097307 \\ -0.232819 & -0.311798 & -0.231333 & 0.149909 & -0.126159 & -0.42633 \\ 0.181935 & 0.579133 & 1.092501 & -0.216914 & -0.031295 & 0.333701 \end{pmatrix} \Delta y_{t-4} + \begin{pmatrix} 4.44E-05 \\ -0.006002 \\ -0.000711 \\ 0.000839 \\ 0.000222 \\ 0.000415 \end{pmatrix} + \varepsilon_t \quad (4)$$

$$\Delta y = [D(LNP) \quad D(LNA) \quad D(LNCO) \quad D(LNE) \quad D(LNG) \quad D(LNI)]' \quad (5)$$

Among the specific estimated coefficient vectors of the VECM error correction model, the first coefficient is illustrated as an example, -1.324 indicates that a change in LNP in period t can eliminate 132% of the disequilibrium error in the previous period to return the disequilibrium state to equilibrium, with a negative error correction coefficient indicating a reverse adjustment effect on the current period value. for example,-0.168526 implies a negative regulatory effect on the price of carbon emissions in the lag period of 1.

Table 5: Overall test table of the VEC model.

Determinant resid covarianc	2.23E-14
Determinant resid covariance	1.21E-15
Log likelihood	675.5579
Akaike information criterion	-11.93738
Schwarz criterion	-5.592398

Table 5 displays the VEC model's overall test results, where the overall log likelihood value of the model is 675.5579, it is large enough. What's more, the AIC and SC values are -11.93738 and -5.592398, which are small enough to indicate that the overall model fits well and has strong explanatory power.

6. Conclusions and Implications

6.1. Conclusion

According to the standardized coefficients cointegration equation, the price of carbon trading is favorably connected with both economic prosperity and the air pollution index, while it is adversely correlated with the rate of industrial development. A long-term equilibrium relationship exists between these variables and the price of carbon.

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6.1.1. Energy costs and carbon trading prices have a positive relationship

LNE_t changes by 1 unit, and LNE_t changes by 1.415010 units. According to equilibrium price theory, Rising coal prices will decrease your consumption of coal, then increase the use of other fuels with less carbon dioxide longevity, finally the demand for carbon emissions will decrease. At this point, Because there is more supply than there is demand, the price will decrease. The empirical study, however, yields a conclusion that differs from the relationship that was expected.

The possible reason for this result is the high dependence on coal in China, the CO2 emission by the use of coal in the same unit is much larger than that emission by other clean energy, so there is much demand for carbon credits. In this situation, the income effect of traditional energy sources such as coal is larger than the substitution effect. When the price rises, the demand increases. Therefore, the empirical results show that there is a positive correlation.

6.1.2. The price of carbon trading is inversely connected with industrial development

LNI_t changes by 1 unit, and LNP_t changes by 6.649311 units. the parameter estimate shows that industrial development has a great impact on carbon trading prices. This indicates that as the development of the industry, the company has made continuous technological progress and improved energy efficiency, reducing the demand for carbon emission rights. At present, China's economic development mode is gradually developing towards capital, manpower and technology intensive development. Reducing carbon emissions through technological progress and improving the energy structure will fundamentally reduce the carbon emissions required, thus reducing the overall demand of enterprises for carbon emission rights.

6.1.3. The price of carbon trading is considerably and favorably connected with macroeconomic development

LNG_t changes by 1 unit, andLNP_t changes by 5.960761 units. According to the fact that heavy industry is the leading industry in China's economic development, the correlation between macroeconomic development and carbon trading price should be consistent with that between industrial development and carbon trading price, but the result is the opposite. that is because the variable selected for the model, the CSI 300 index, has a majority weight in the financial real estate sector (45.46%) and only 9.83% in the industrial sector. From the perspective of the whole society's economic development, each industrial sector expands production and produces more CO_2, which increases the demand for carbon emission rights. So the price of carbon emission rights increases with economic prosperity.

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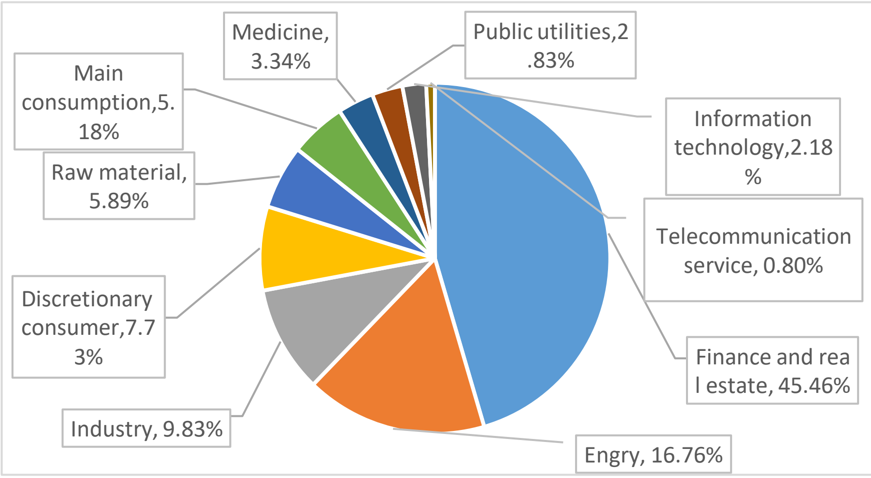

Figure 2: CSI 300 index sector weighting distribution.

6.1.4. Air quality is positively correlated with the price of carbon emission trading.

There is a more obvious association between air quality and the price of carbon credits, with a positive correlation. LNA_t changes by 1 unit, and LNP_t changes by 0.038155 units. The larger AQI value represents, the worse air quality. This suggests that as the air quality deteriorates, the government steadily increases environmental protection awareness and tightens carbon emission regulations, increasing demand for carbon emissions and driving up the price of carbon emissions trading.

6.2. Implications

6.2.1. Improve the traditional energy structure, and the carbon market price mechanism.

The empirical results show that the income effect of coal price changes is greater than the substitution effect, which means that higher coal prices will lead to higher coal demand and higher carbon trading prices. In addition, A large amount of carbon dioxide produced during the combustion of traditional energy such as coal will cause environmental pollution. Improving China's traditional energy structure, reducing the dependence on traditional energy with high energy consumption, and vigorously promoting clean energy can moderately stabilize the demand for carbon emissions.

6.2.2. Enhance the carbon emission trading system by keeping track of and making real-time adjustments to the carbon trading price.

According to the empirical findings, several variables have an equilibrium relationship with the price of carbon emission trading over the long run, but there are unstable variables in the short term, and the variables will depart from the equilibrium over time. From this viewpoint, China's carbon trading market is not ideal in terms of price mechanism, market system, and participation level when compared to wealthy nations. An efficient carbon trading market should be formed as soon as possible. Only by forming a strict legal and regulatory control system for the carbon trading market can we achieve the balance between carbon emission reduction and economic development.

6.2.3. Encourage low-carbon technology innovation and promote the technological progress of enterprises.

According to the analysis of the empirical results, in the process of industrial development, technological progress can promote enterprises to adopt low-carbon environmental technologies, improve energy use efficiency and reduce carbon emission demand. Therefore, the state should issue policies to encourage enterprises to innovate in low-carbon technologies, such as reducing environmental protection taxes for enterprises with low-carbon technology patents, and giving corresponding incentives to enterprises that actively use energy-saving technologies. Enterprises should also increase investment in low-carbon technologies and actively undertake social responsibility for emission reduction.

6.2.4. Enhance environmental protection awareness and improve air quality.

The empirical results show that the effect of air quality on carbon price is significantly and positively related. If air quality decreases, the government will strengthen environmental management and strictly control carbon emissions, which will affect the price of carbon. What's more, since the "carbon peak" target is a huge challenge for China, the whole society needs to work together to achieve this goal. Therefore, the government should put forward effective emission reduction policies in combination with the actual situation of development strategies. The public should enhance environmental awareness, control production, and domestic emissions.

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