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Analysis of Heterogeneity of Carbon Trading Price Influencing Factors in China's Carbon Trading Pilots

-- Taking China's Seven Carbon Trading Markets as an Example

Xunyang Li*, Xinxin Guo

School of Finance, Anhui University of Finance and Economics, Bengbu, China

*1747418404@qq.com

Abstract

This study analyzes the influencing factors and heterogeneity of carbon trading prices (CTPs) in China's seven major carbon trading pilot markets. With the intensification of climate change issues, carbon trading has received widespread attention as an important market mechanism. Through empirical analysis of monthly data from January 2014 to December 2023 in seven pilot markets: Shenzhen, Shanghai, Beijing, Tianjin, Guangdong, Hubei and Chongqing, a dynamic heterogeneous panel PMG model was used to explore the impact of factors such as energy prices, macroeconomic activity and environmental quality on CTPs. Based on these results, this paper puts forward targeted policy recommendations, including formulating differentiated carbon trading policies, strengthening environmental governance, and deepening research on the carbon trading market, in order to promote low-carbon transformation and the stable development of the market.

Keywords

Carbon trading, PMG model, heterogeneity analysis.

1. Introduction

Severe climate change has become an important topic of global concern, and the serious consequences of climate change and its disastrous economic and social impacts are forcing all countries and regions to work together to find new solutions to mitigate climate change and reduce carbon dioxide emissions[7] . The signing of the Kyoto Protocol in 1997 and the Copenhagen Accord in 2009, followed by the 2015 Paris Climate Change Conference, reflecting the active participation of countries in climate governance and their efforts to mitigate climate change. The International Energy Agency (IEA) report concluded that "without China, there is no reasonable pathway to limit global temperature rise to 1.5 degrees Celsius" (2020)[14] . Therefore, it is particularly important to conduct an in-depth study of the development of the carbon trading pilot market and the key influencing factors of the carbon trading price (CTP) at the stage of full nationwide operation. This will constitute the main research object of this paper.

At present, China has successively set up eight pilot carbon emissions trading centres. As of 2021, China's carbon emissions trading market covers more than 20 industries, nearly 3,000 key emitting enterprises and 620 million tonnes of carbon emissions. The cumulative transaction amount is about RMB 17.936 billion, which is the widest coverage of CO2 emissions in the world However, compared with mature overseas carbon markets such as the European Union's Carbon Emissions Trading System (ETS), China's pilot market still has the problem of asynchronous development. The CTP data of China's pilot market is incomplete and has the typical characteristic of small information[13] . At present, the carbon trading market still suffers from insufficient trading dynamics and unstable trading prices. Existing studies argue

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that highly volatile markets increase the risk of loss and threaten the incentive to reduce carbon emissions[14] .

Compared with foreign carbon trading systems, carbon trading in China started relatively late. in October 2011, the National Development and Reform Commission (NDRC) approved the launch of carbon trading pilots in seven provinces and municipalities: beijing, Shanghai, tianjin, chongqing, hubei, guangdong, and shenzhen. in 2016, fujian province opened its eighth carbon market pilot. the pilot market in fujian province is expected to be completed by the end of this year. So far, China has established a carbon trading system based on eight local carbon trading trials. However, it should be noted that due to the late start, Chinese carbon trading enterprises currently have problems such as low level of information disclosure[9] , in order to collect enough data for the research and analysis, the research object of this paper focuses on the seven earliest carbon trading pilots set up in China. In analysing the influencing factors of CTP, the literature mainly focuses on energy prices, macroeconomic activities and environmental conditions. However, these factors differ in terms of factor selection, temporal or spatial dimensions and do not necessarily lead to consistent conclusions[14] . The significance of this paper's study is to explore the heterogeneity of the influencing factors of different carbon trading markets using a multi-pilot, multi-indicator approach and to target meaningful recommendations for the development of each pilot based on the results of the empirical analyses.

In summary, in order to understand the uniqueness of the carbon price formation mechanism in the Chinese market and the potential forces behind it, this paper analyses and proposes three hypotheses related to the carbon price mechanism, and conducts an empirical study using a dynamic heterogeneous panel PMG model using the available monthly data from the seven pilot markets of Shenzhen, Shanghai, Beijing, Tianjin, Guangdong, Hubei, and Chongqing from January 2014 to December 2023.

The structure of this paper is organised as follows: section 2 is a literature review. Part 3 provides an analysis of the theoretical mechanisms of the impact of factors on CTP and presents the research hypotheses. Section 4 analyses the carbon emissions trading market, including its current situation and development issues. Section 5 describes the construction of the empirical model and the empirical analysis of the factors influencing CTP, including empirical tests and results. Section 6 presents the conclusions and policy implications.

2. Literature Review

Carbon trading, as an important market mechanism to cope with climate change, has attracted widespread attention in recent years. Gao Kai et al. (2024) explored the effect of carbon emissions trading on the improvement of regional environmental pollution, and empirically examined seven pilot provinces and cities using the synthetic control method[1] . Luo Liangwen et al. (2024) analysed the impact of pilot carbon emissions trading on the low-carbon transformation of urban industry, emphasising the necessity and effectiveness of policy implementation[2] . In addition, Sun Xia and Liang Hongzhi (2024) point out that carbon trading provides a new channel for local governments to increase revenue, demonstrating the economic benefits of the policy[3] . In the wider literature, Ji et al. (2019) systematically sorted out the research on carbon price in carbon emissions trading system through bibliometric analysis, revealing the research trends and hotspots in the field[8] . Existing literature generally agrees that carbon trading has multiple advantages, and Wuzheni et al. (2024) studied the spillover effect of carbon trading policy, pointing out its positive role in transferring the responsibility for implied carbon emissions between regions, and promoting inter-regional co-operation and co-ordination[4] . Xu Junwei and Liu Zhihua (2024) emphasised the importance of the carbon trading pilot policy in promoting the transformation of energy consumption

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structure and the development of regional low-carbon economy[5] . KaileZhou and YiwenLi (2019), on the other hand, explored the influencing factors and fluctuating characteristics of China's carbon emissions trading price, pointing out the importance and potential advantages of carbon trading in the market mechanism[10] .

Regarding the influencing factors of carbon trading prices, a variety of indicators have been proposed in the literature.Yin et al. (2019) analysed a variety of factors affecting carbon trading prices, including market supply and demand, policy environment and economic growth[13] . BeibeiShi et al. (2022) explored the relationship between market incentives, quota allocation and emission reduction effects, and emphasised the impact of policy design on market prices [7] . Zeng et al. (2023) further analysed the influencing factors of carbon trading prices in the context of "dual-carbon", and proposed a more detailed analytical framework[14] . KaileZhou and YiwenLi (2019) also conducted an in-depth study on the volatility characteristics of carbon trading prices. Various influencing factors are proposed, including market sentiment and policy changes[10] . Among the numerous studies in the literature, the heterogeneity among the pilots is the focus of the research.Jiang et al. (2022) investigated the impact of corporate application of blockchain technology in eight carbon trading pilots, and found that there were differences in the degree of technology application and market response in different regions[9] . Yan et al. (2024) explored the market price forecasts of different pilots through elliptic factor analysis, revealing inter-regional differences[12] . In addition, Song et al. (2022) analyzed the carbon trading price influencing factors of different pilots based on an improved grey correlation analysis model, which further verified the influence of regional characteristics on market price[11] .

There is some consensus in the existing literature on the direction of influence of factors that affect carbon trading prices. Most studies show that factors such as market supply and demand, policy incentives and technological innovation have a positive impact on carbon trading prices. For example, Yin et al. (2019) point out that an increase in market demand drives up carbon trading prices[13] . However, some studies also mention that market friction and uncertainty may lead to price volatility, creating a negative impact.KaileZhou and YiwenLi (2019) also point out in their study that fluctuations in market sentiment may have a negative impact on carbon trading prices[10] .

In summary, although existing studies provide important perspectives for the understanding of carbon trading, there are still some shortcomings. Most of the literature focuses mainly on descriptive analyses of individual pilots and lacks systematic comparisons and comprehensive analyses between different pilots. This limitation may lead to a lack of comprehensive understanding of the effects of carbon trading policies, and future research should pay more attention to cross-regional comparative studies to reveal the performance and impacts of carbon trading in different contexts

3. Theoretical Assumptions

Based on the above literature review, this paper provides three theoretical hypotheses regarding the mechanisms by which factors influence CTP.

Fluctuations in the CTP reflect changes in the equilibrium between supply and demand in carbon emission allowances. Therefore, the factors affecting this balance represent the key to analysing the theoretical mechanisms, including environmental factors, energy price factors and macroeconomic factors. These are all important for energy conservation and emission reduction, which is important for achieving China's "dual-carbon" goal.

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3.1. Impact of energy prices on carbon trading prices

In China's carbon trading market, the volatility of energy prices significantly affects carbon trading prices.Yin et al. (2019) point out that market supply and demand and energy prices are important factors affecting the price of carbon emissions trading[13] . In addition, KaileZhou and YiwenLi (2019) also emphasised the impact of energy price volatility on carbon trading prices, pointing out that market sentiment and policy changes can exacerbate this impact[10] , and that an increase in energy prices will lead to an increase in carbon trading prices.

Hypothesis 1: Energy prices have a positive effect on carbon trading prices

3.2. Macroeconomic impact on carbon trading prices

There are significant differences in the impacts of macroeconomic activities on carbon trading prices in different regions.The study of KaileZhou and YiwenLi (2019) echoes this by emphasising the impacts of market sentiments and economic activities on carbon trading price volatility[10] . In addition, Jiang et al. (2022) further verified the heterogeneity of the impact of macroeconomic activities on carbon trading prices through theoretical analyses, pointing out that there are differences in the degree of technology application and market responses in different pilot markets, and that the impact of macroeconomic activities on carbon trading prices shows significant heterogeneity in different pilot markets[9] .

Hypothesis 2: There is heterogeneity in the impact of macroeconomic factors on carbon trading prices

3.3. Impact of environmental quality on carbon trading prices

The deterioration of environmental quality significantly inhibits carbon trading prices. Gao et al. (2024) point out the importance of environmental factors in the carbon market, reflecting the public's concern about environmental quality and the pressure on policymakers to deal with air pollution[1] . In addition, Zeng et al. (2023) also emphasised the impact of environmental quality on carbon trading prices in the context of "dual-carbon", pointing out that the implementation of environmental policies can effectively promote the healthy development of the carbon market, and that the deterioration of environmental quality will significantly reduce the price of carbon trading[14] .

Hypothesis 3: Environmental quality has a negative impact on carbon trading prices

4. Research Design

In order to comprehensively analyse the operational mechanisms of China's seven carbon trading markets (CTPs), this study constructs a base model to empirically test the proposed hypotheses. Specifically, a dynamic heterogeneous panel PMG model is used for the analysis, which involves various aspects of variable selection, data sources, model construction and empirical analysis.

4.1. Variable selection and data sources

4.1.1. Sample selection

In this paper, we have chosen a large sample size, including both temporal and spatial dimensions, and we have also theoretically sorted out the factors influencing CTP.

(1)CTP. The carbon trading prices in the seven major carbon trading markets of Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, and Chongqing from January 2014 to December 2023 are used as the explanatory variables to explore the impact of four major categories of indicators, namely, the international economic situation, the energy price factor, and the world economy, on CTP. (Literature cited)

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(2) Stock indexes: the domestic economic situation mainly includes gross domestic product, price level, investment, savings, consumption, import and export indicators, the establishment of the carbon trading market will have a certain impact on social production and social development, and the macro-economic relationship between the inextricable link between the high and low economic growth rate and the expectation of optimism or not for the impact of carbon trading prices are not the same effect. In this paper, we select several stock indices from January 2014 to December 2023, including the Shanghai Stock Exchange Index, Shenzhen Index, Energy Index, Raw Material Index, Industrial Index, and Bond Yield, to represent the trend of the domestic economy.

(3) Energy prices: In daily life and production, common energy sources include oil, coal, natural gas, electricity, etc. The prices of these energy sources will directly determine the total amount of carbon emissions and lead to fluctuations in the price of carbon emissions trading by influencing the total amount of socio-economic development, the industrial structure and the intensity of energy and other factors. In this paper, the raw coal price (yuan/tonne), steel price (yuan/tonne), mineral iron ore price (yuan/tonne), liquefied natural gas price (yuan/tonne), gasoline price (yuan/tonne) and crude oil price (yuan/tonne) are chosen to represent the energy price category factors from January 2014 to December 2023, in which the price of raw coal is chosen to be the price of Dongsheng in Inner Mongolia, and the gasoline price is chosen to be the price of No. 95 gasoline;

(4) U.S. stock indices: The starting point of carbon financial market construction is based on international cooperation to jointly deal with the problem of environmental pollution, and the establishment and development of carbon emission markets in various countries and regions are inseparable from the overall economic environment of the world. Although China's carbon financial market started late, the rapid development of the national economy has made its volume increasing, and the potential for growth is also constantly apparent, while the impact of the world economic environment is also increasing. The United States as the world's largest economy, its impact on the Chinese economy is the most enormous, this paper selects the Nasdaq index and the Dow Jones index from January 2014 to December 2023 on behalf of the world economy, to explore its impact on the CTP.

4.1.2. Data sources

The data in this paper comes from Wind database, CTP comes from China Carbon Trading Network, indicators are selected with reference to Zeng et al. (2023), and related variables are defined as follows:

4.2. Modelling

4.2.1. Empirical model setting

The data selected in this paper include both time and space dimensions, which are typical panel data. After the experiments of the model, comparing the R2 and t-statistics of different models, it is finally found that linear regression fits the best.

$$\mathrm{PRICE_{it}} = \beta_0 + \beta_1 \mathrm{SCI_{it}} + \beta_2 \mathrm{SZCI_{it}} + \beta_3 \mathrm{EI_{it}} + \cdots + \beta_{13} \mathrm{NCI_{it}} + \beta_{14} \mathrm{DJIA_{it}} + \varepsilon \qquad (1)$$

PRICE represents the closing price of carbon trading for each carbon trading pilot, i represents each pilot province, and t represents the effective trading day, respectively.

4.2.2. Descriptive statistics of variables

In this paper, the collected data were analysed using python 3.7, and the raw data for each indicator were processed with unit transformation to unify the dimensions between the explanatory and interpreted variables, and the descriptive statistics of the data are shown in the table below.

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Table 1. Variable Definitions

Variable category	variable name	Variable Abbreviations
explanatory variable		
prices	Shenzhen Carbon Trading Price	SHENZHENG
	Shanghai Carbon Trading Price	SAHNGHAI
	Beijing Carbon Trading Price	BEIJING
	Guangdong Carbon Trading Price	GUANGDONG
	Tianjin Carbon Trading Price	TIANJING
	Hubei carbon trading price	HUBEI
	Chongqing Carbon Trading Price	CHONGQING

explanatory variable		
stock market index	SSE (Shanghai Stock Exchange)	SCI
	SSE (Shenzhen Stock Exchange) index	SZCI
	Energy index	EI
	Raw material index	MI
	industrial index	II
energy price	bond proceeds	BY
	raw coal price	RCP
	steel prices	SP
	Price of Ore and Iron	IOP
	Liquefied natural gas prices	LNG P
	petrol price	GP
	crude oil price	COP
US stock market index	NASDAQ (stock exchange)	NCI
	Dow Jones industrial average (Wall street stock market index)	DJIA

Table 2. Descriptive statistics for variables

	mean	std	min	max	abs
PRICE	32.80	23.46	0.00	138.00	840
SCI	3102.76	433.87	2026.36	4611.74	840
SZCI	10946.09	2084.65	7189.58	16100.45	840
EI	994.99	263.93	509.70	1683.41	840
MI	3245.03	678.46	1944.92	5169.47	840
II	3977.54	856.90	2121.12	7209.57	840
BY	127.44	14.48	98.31	153.03	840
RCP	438.05	266.85	107.50	1469.50	840
SP	3600.50	886.67	1725.33	5768.89	840
IOP	477.64	386.77	0.00	1488.78	840
LNGP	4266.87	1479.23	0.00	8437.20	840
GP	3502.51	4052.17	0.00	10206.00	840
COP	63.95	19.79	19.09	115.26	840
NCI	8604.20	3568.57	4103.88	15644.97	840
DIIA	25370.13	6578.51	15698.85	37689.54	840

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5. Empirical Testing

5.1. Correlation analysis

In order to test whether the variable's will have an impact on the regression results, before the regression started, the variable indicators were analysed for correlation and the results of the correlation test are shown in the table below.

Based on the correlation matrix, it can be observed that although there are several significant correlations between the variables, none of the correlation coefficients exceeds the threshold usually associated with strong multicollinearity (which is generally considered to be above 0.8). For example, the highest correlation occurs between the SZCI and the NASDAQ Composite Index (NCI) (0.556), followed by the Commodity Prices (COP) and the SZCI (0.445), and the Dow Jones Index (DJIA) and the NASDAQ Composite Index (NCI) (0.566). These values indicate a moderate correlation rather than a strong correlation. Other variables, such as the average price of carbon trading transactions (PRICE), the Shanghai Stock Exchange Index (SCI), and the liquefied natural gas price (LNGP) have relatively low correlations with each other, further suggesting that these variables can be treated as independent predictors in the regression model, and that there is no strong correlation between the variables.

Table 3. Correlation test results

	PRICE	SCI	SZCI	EI	MI	II	BY	RCP	SP	IOP	LNGP	GP	COP	NIC	DJIA
PRICE	1.000														
SCI	-0.007	1.000													
SZCI	0.044	0.573	1.000												
EI	0.240	0.114	0.131	1.000											
MI	0.087	0.543	0.563	0.452	1.000										
II	0.045	0.618	0.604	0.174	0.597	1.000									
BY	0.341	0.311	0.401	0.621	0.461	0.303	1.000								
RCP	0.328	0.252	0.372	0.608	0.580	0.336	0.604	1.000							
SP	0.136	0.125	0.276	0.551	0.369	0.011	0.620	0.513	1.000						
IOP	0.161	0.112	0.211	0.308	0.204	0.091	0.338	0.308	0.309	1.000					
LNGP	0.168	0.009	0.094	0.481	0.269	0.063	0.233	0.483	0.415	0.063	1.000				
GP	0.258	-0.269	-0.147	0.640	0.098	-0.126	0.154	0.478	0.369	0.167	0.543	1.000			
COP	0.350	0.239	0.445	0.512	0.423	0.229	0.648	0.540	0.585	0.332	0.430	0.296	1.000		
NCI	0.304	0.360	0.556	0.544	0.569	0.326	0.606	0.525	0.558	0.399	0.332	0.282	0.563	1.000	
DJIA	0.315	0.316	0.439	0.525	0.513	0.268	0.631	0.559	0.603	0.370	0.357	0.322	0.544	0.566	1.000

As shown in the table below, based on the results of the variance inflation factor test, it is further shown that the VIF between the indicators of the variables that have been toughened are less than 10, indicating that there is no multicollinearity between the variables.

5.2. Cross-sectional correlation test results

The CD statistic is used to test for correlation between cross-sections. Under the original hypothesis of "no cross-sectional correlation", the CD statistic follows an asymptotic standard normal distribution. According to the test results shown in the table below, the original hypothesis can be rejected at the 1% significance level for all variables. This result indicates that there is a significant correlation between the cross-sections in the sample, suggesting that the effect of this factor on model estimation needs to be considered in subsequent analyses.

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Table 4. VIF test results

Variable	VIF
PRICE	1.0000
SCI	1.2654
SZCI	3.4695
EI	6.6992
MI	8.5682
II	5.8370
BY	4.4164
RCP	6.5546
SP	8.9734
IOP	6.0208
LNGP	1.2635
GP	2.1291
COP	5.3506
NCI	7.4545
DJIA	5.4368
PRICE	7.9240

Table 5. Cross-sectional correlation test results

Breusch-PaganLM	69.088	0.000
PesaranCD	201.993	0.000

5.3. Unit Root Test Results

Due to the strong cross sectional correlation of the panel data used in this paper, unit root tests were conducted for all variables.

Table 6. Unit Root Test Results

Variable	statistic	P	D_Variable	D_Statistic	D_P
PRICE	-3.051	0.030	D. PRICE	-3.051	0.030
SCI	-7.852	0.000	D. SCI	-7.852	0.000
SZCI	-6.276	0.000	D. SZCI	-6.276	0.000
EI	-9.061	0.000	D. EI	-9.061	0.000
MI	-6.916	0.000	D. MI	-6.916	0.000
II	-7.400	0.000	D.II	-7.400	0.000
BY	-4.585	0.000	D. BY	-4.585	0.000
RCP	-6.763	0.000	D. RCP	-6.763	0.000
SP	-5.063	0.000	D. SP	-5.063	0.000
IOP	-3.438	0.010	D. IOP	-3.438	0.010
LNGP	-5.525	0.000	D. LNGP	-5.525	0.000
GP	-4.607	0.000	D. GP	-4.607	0.000
COP	-6.418	0.000	D. COP	-6.418	0.000
NCI	-4.130	0.001	D. NCI	-4.130	0.001
DJIA	-4.453	0.000	D. DJIA	-4.453	0.000

According to the statistical results provided, all the variables have significantly lower statistics than the critical values and the corresponding p-values are less than 1% level of significance.

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This indicates that except for PRICE (P=0.0304) and IOP (P=0.0097), all the other variables such as SCI, SZCI, EI, MI, II, BY, RCP, SP, LNGP, GP, COP, NCI and DJIA have P-values of 0.0000 or close to 0, showing strong statistical significance. Therefore, it can be inferred that there is no unit root for these variables, implying that they are smooth. Whereas, the P-values of PRICE and IOP are less than 0.05 but still higher than 0.01, implying that there may be a unit root for these two variables, suggesting that they may be non-smooth. Non-stationary variables may lead to pseudo-regression phenomenon in time series analysis, thus affecting the validity and reliability of the model. Therefore, to overcome the problem of non-stationary data and significant correlation between cross-sections in the subsequent analyses, dynamic panel PMG was used to estimate the model.

5.4. Dynamic heterogeneous panel PMG model results

Due to the panel data in this paper are characterised by non-stationarity, cross-sectional correlation, long periods and relatively few cross-sections (N=7, T=840), traditional fixed and random effects cannot be effectively estimated.

Unobservable factors, such as institutions and cultures that exhibit systematic differences across regions, will not only affect the intercept of the regression but also the sensitivity of the explanatory variables to the explanatory variables. Endogenous problems and individual heterogeneity in these problems will greatly affect the correctness and validity of the model estimation results, so these problems need to be corrected by dynamic panel models. In this paper, we try to construct a dynamic panel model using lagged terms of explanatory variables under equilibrium conditions to estimate the dynamic adjustment of each factor affecting CTP.Pesaran proposed that the PMG method can effectively solve the problem of coefficient heterogeneity in the process of dynamic panel estimation. Therefore, the lagged terms are considered in the model and simultaneous short- and long-run investigations are conducted using a dynamic heterogeneous panel PMG model. This is useful in analysing the long- and short-term influences on CTP.

The long-run relationships between the constraint variables of the PMG model are consistent, and the short-run coefficients and the coefficients of the error correction terms are allowed to differ between cross-sections. To better achieve an effective balance between long-run consistency and short-run heterogeneity.

The impact of IND on CTP is shown to be positive and significant in all time frames, suggesting that industrial development has a sustained positive driving effect on carbon trading prices (CTP). This finding emphasises the importance of industrial activities in the carbon market and may reflect the industrial sector's demand for carbon emissions and reliance on carbon trading mechanisms. Based on the results of the unit root test, unit roots exist for both GAS (natural gas) and COAL (coal), so first order differences are introduced into the model to ensure smoothness. For natural gas, the impact is negative in the long run, while it is positive in the short run. This may indicate that while the use of natural gas may increase in the short term due to market demand or policy incentives, in the long term its impact on the price of carbon trading may be constrained by other factors such as market saturation or competition from alternative energy sources.

The consistently positive impact of coal reflects the fact that China's reliance on traditional energy sources in its energy mix is still high, and that the substitution of cleaner energy sources has not yet significantly altered this status quo. This phenomenon may be closely related to China's energy policy, market demand, and the importance of coal in energy consumption. In addition, the negative effect of AQI (Air Quality Index) is consistent with Hypothesis 3, suggesting that deteriorating air quality may have a dampening effect on carbon trading prices. This result emphasises the importance of environmental factors in the carbon market and may

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reflect public concern about environmental quality and the pressure on policy makers to respond to air pollution.

Table 7. PMG test results

variable	Shenzhen		Shanghai		Beijing		Guangdong		Tianjin		Hubei		Chongqing	
	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
const	126.954	2.477	-164.847	-3.594	-56.012	-1.282	-128.709	-3.374	75.301	2.540	-74.266	-3.268	-13.708	-0.354
SCI	-0.010	-0.601	0.032	2.164	0.017	1.230	0.005	0.405	-0.007	-0.699	0.025	3.569	-0.002	-0.169
SZCI	0.001	0.182	-0.003	-0.936	0.003	1.041	-0.001	-0.586	0.003	1.401	-0.005	-3.792	0.000	0.057
EI	0.008	0.494	-0.006	-0.381	-0.012	-0.892	-0.027	-2.258	-0.019	-2.058	-0.028	-3.839	0.008	0.690
MI	-0.020	-1.756	-0.029	-2.885	-0.019	-2.022	0.006	0.693	-0.002	-0.343	0.011	2.272	0.003	0.398
II	0.011	1.213	0.007	0.835	-0.007	-0.870	-0.004	-0.561	-0.003	-0.496	-0.008	-2.039	0.000	-0.065
BY	-0.544	-1.217	1.326	3.312	1.049	2.751	1.307	3.927	-0.242	-0.932	0.711	3.593	0.325	0.960
RCP	0.031	2.196	-0.009	-0.736	0.056	4.623	0.019	1.771	0.025	3.037	0.013	2.040	-0.002	-0.219
SP	-0.019	-4.127	0.005	1.196	-0.005	-1.361	-0.007	-1.962	-0.012	-4.468	-0.003	-1.346	0.001	0.208
IOP	0.005	1.321	-0.001	-0.220	0.007	2.184	0.005	1.782	0.005	2.229	0.002	1.384	0.000	-0.138
LNGP	0.001	0.971	0.002	1.409	-0.003	-3.269	0.000	0.220	0.000	0.281	0.001	1.471	0.001	0.834
GP	0.237	1.626	0.527	4.040	0.274	2.204	0.897	8.261	0.225	2.670	0.313	4.840	-0.068	-0.618
COP	-0.001	-1.672	0.000	-0.068	0.000	0.255	0.001	1.404	0.001	2.054	0.000	0.704	0.002	3.017
NCI	0.001	0.576	-0.001	-0.249	-0.004	-1.933	0.000	0.150	0.002	1.243	0.001	0.929	0.003	1.452
DJIA	0.002	0.929	-0.001	-0.479	0.001	0.820	-0.001	-0.951	0.000	0.065	-0.001	-0.812	-0.002	-1.742

According to the results of the PMG model analysis, the significant estimates reveal that the influence of the variables on carbon trading price (CTP) shows heterogeneity among different provinces and cities. In Shanghai, both SCI (Shanghai Stock Index) and BY (Bond Yield) show significant positive impacts of 0.032 and 1.326, respectively, suggesting that these two variables play an important role in driving the carbon trading price, which may reflect the market's positive expectations of stock and bond returns. In addition, the significant positive effect of RCP (raw material price) in Beijing (0.056) further emphasises the driving effect of raw material price volatility on the carbon market. In Guangdong, the significant positive effect of BY (1.307) similarly indicates the positive contribution of bond market activity to carbon trading prices. Comparatively, the significant negative impacts (-0.019 and -0.012) of SP (steel price) in Shenzhen and Tianjin suggest the inhibitory effect of steel industry volatility on the carbon trading market, reflecting the supply-demand imbalance within the industry or the impact of policy regulation.

6. Conclusions and Suggestions

This study explores the influencing factors of carbon trading price (CTP) and its heterogeneity by empirically analysing seven carbon trading pilot markets in China. The findings show that there are significant regional differences in the influence of energy prices, macroeconomic activities and environmental quality on carbon trading prices, validating the three theoretical hypotheses proposed in this paper. Specifically, fluctuations in energy prices generally have a positive impact on carbon trading prices, especially in regions relying on traditional energy sources; the impact of macroeconomic activities shows significant heterogeneity across pilot markets, with regions with rapid economic development being more sensitive to carbon trading prices; and deterioration in environmental quality significantly inhibits carbon trading prices, reflecting public concern about environmental issues and policy makers' pressure. Based on the above conclusions, this paper puts forward the following recommendations: first, targeted development of pilot policies. It is recommended that policymakers take into full consideration the energy structure and economic development level of each region when formulating carbon trading policies, and formulate differentiated policies to more effectively promote low-carbon transition and the stable development of the carbon market. Second, strengthen environmental governance. While promoting the development of the carbon market, the government should strengthen environmental governance measures and improve air quality to enhance public support for and participation in carbon trading policies, which will in turn promote the enhancement of carbon trading prices. Third, deepen research and data collection. Future research should further explore other potential influencing factors and their interactions, especially in different pilot markets, and it is recommended to strengthen long-term monitoring and data collection of the carbon trading market to enrich the understanding of the carbon trading price formation mechanism.

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