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THE DRIVING RELATIONSHIP OF CHINA CARBON PRICE BASED ON DIFFERENT MARKET VOLATILITY STATES

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ABSTRACT

The China carbon market is a market-oriented designation for addressing climate issues. Price mechanism is the core of carbon market, studying on the price formation can promote the emission reduction targets. This article conducts an autoregressive adjusted Markov model to classify the carbon price state, and designs a multiple regression model to test the driving mechanism. The results show the second order autoregressive Markov model of MS(2)-AR(2) model can classify the carbon price into high and low volatility states. Furthermore, in high volatility state, carbon price is only significantly positively correlated with macroeconomic factors of China Securities Index 300 (CSI300) and European carbon price of European emission allowance future contract (EUAF), while in low volatility state, carbon price is significantly positively influenced by energy market products JM future (JMF) and Oil, macroeconomic factor of CSI300, and European carbon price of EUAF. Furthermore, the impact strength is weaker than the whole sample regression results. The results provide reference for investors to judge carbon price and reveal price trends.

Keywords: China carbon price, Carbon market, Market volatility state, MS(k)-AR(q) model, Price driving relationships

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INTRODUCTION

As the enhancement of global climate problems and environmental protection awareness, effectively curbing carbon emissions has become a key issue that needs to solve urgently. As one of the world's largest carbon emitting countries, China's cumulative carbon emissions in 2022 amounted to 11 billion tonnes, that accounting for 28.87% of global emissions according to the China emission accounts and datasets (CEADs). Among them, industrial emissions amounted to 4.2 billion tonnes, accounting for 38.18% of China's emissions. While the steel industry with the highest carbon emissions among the 31 categories of manufacturing contributes to 15% of China's total emissions.

The heavy reliance on fossil energy consumption has become an obstacle to the economy high quality development in China. Therefore, to address the contradiction between economic development and environmental sustainability, the Chinese government proposed the carbon peak and carbon neutrality strategy at the 75th United Nations General Assembly in September 2020. That is the China aim to have carbon dioxide emissions peak before 2030 and achieve carbon neutrality before 2060. As a specific measure of the proposed strategy, the Chinese government officially launched a nationwide carbon trading market operation in 2021 after conducting the regional carbon trading pilot projects. Generally, the trading mechanism of the carbon market is regarding the carbon emission rights as a scarce commodity for trading in the market, which encourages enterprises with low emission reduction costs to exceed their reduction targets, and sell excess emission allowance to enterprises with high emission reduction costs, and final help the latter meet emission reduction requirements and reduce the total carbon emissions cost (Byun & Cho, 2013; Liu et al., 2023). According to the data disclosed by the national carbon emissions trading market, as of October 2023, the cumulative trading volume of Chinese emission allowance (CEA) were 365 million tonnes, with a cumulative trading volume of 19.437 billion yuan.

After two years of construction, the overall operation of China carbon emission trading market has been stable, the role of price discovery has begun to show, and the enterprises have significantly enhanced their emission reduction awareness, the desired construction goals have been basically achieved. The price mechanism is the core of carbon market (Yun et al., 2023). To improve the price mechanism in curbing pollutant emissions and perfecting emission reduction efficiency, the main task of this article are studying the market price formation and driving mechanism, revealing the formation process of complex carbon price and exploring the impact relationship of various influencing factors on carbon price. Specifically, we focus on studying the carbon price driving process under different market volatility states, so as to provide new explanatory evidence for the formation of carbon premium.

LITERATURE REVIEW

Regarding the carbon price formation mechanism, previous studies mainly focus on revealing the carbon price driving process from the points of energy prices, macroeconomic factors and prices of similar products.

Firstly, in term of energy prices, the carbon allowance demand by polluting enterprises mainly depends on their carbon emissions. If the carbon allowances are relatively small compared with the actual or expected shares, the polluting enterprises will buy more allowances, and then promote the carbon price (Oberndorfer, 2009). Electricity companies are the main buyers of the carbon market, and their trading behaviour has a significant impact on carbon price (Boersen & Scholtens, 2014). The consumption of fossil fuels is directly related to the carbon emissions, and final affects the carbon price. The rising fossil energy prices will promote the carbon price, and a decreasing price will also lead to a declining carbon price (Lin & Jia, 2019; Hammoudeh et al., 2014). The impact of energy products with different carbon emission intensities on carbon price also varies (Lilliestam et al., 2021). If the coal price rise, polluting enterprises will shift towards using cleaner energy such as oil and natural gas, resulting in lower carbon allowance demand and final reducing the carbon price (Jie et al., 2021; Anke et al., 2020). Wen et al. (2022) used the cointegration test method to find a cointegration relationship between energy price and carbon price, the oil price has the most significant impact on carbon price, followed by the price of natural gas and coal. In China, coal is the main source of carbon emissions. In this regard, Wang et al. (2024) conducted a hybrid generalised autoregressive conditional heteroskedasticity (GARCH) model and found that the coal prices and economic policy uncertainty have produced asymmetrical impacts on carbon prices.

Secondly, in terms of macroeconomic factors, the macroeconomic impact the production and operation of polluting enterprises, which in turn affects the supply and demand of carbon allowances, triggers the change of carbon price (Lyu et al., 2020; Wen et al., 2020). Carbon market is operating along with the economic activities (Jang et al., 2024). When the macroeconomic trend is strong, polluting enterprises will expand their production, leading to an increase in carbon emissions and carbon allowance demand, which in turn, raising the carbon price. On the contrary, when the economy is relatively sluggish, for example the COVID-19 pandemic has produced a huge damage on the carbon market, the enterprises production activities are less, the corresponding carbon emissions and carbon allowances are decreasing, the carbon price is decreasing (Christiansen et al., 2005; Yang et al., 2024; Zhao et al., 2023). Research indicated that the stock prices are an important indicator reflecting the macroeconomic and are closely related to the carbon market (Chevallier & Sevi, 2011; Ren et al., 2023). Lutz et al. (2013) studied the relationship between the price of European carbon emission allowance (EUA) and stock market, and a positive correlation between stock prices and carbon price has been detected. Using a multivariate GARCH model, Oberndorfer (2009) pointed out that the price change of EUA is positively correlated with the stock price of electricity companies, while the stock price change does not affects the EUA price.

Thirdly, previous studies found correlation between carbon markets of different regions. As the China carbon market was established relatively late, although the carbon market has developed rapidly, the marketisation mechanism has not mature enough, as a result, it inevitably be affected by spillover effects from the European carbon market, and the European carbon price showed an impact on China carbon price. When the European carbon price is decreasing, the enterprises production cost is also decreasing, so the export-oriented enterprises will expand production and export (Convery & Redmond, 2007), as a result, the Chinese enterprises will face greater competitive pressure, leading to significant reduction in production and carbon emissions, and final the carbon price is decreasing. A positive correlation between European carbon price and China carbon price has been detected in recent studies of Gao et al. (2023) and Wang et al. (2023).

In summary, previous scholars have conducted extensive research on the carbon price driving mechanism, that provide abundant foundation for this article. However, these studies may ignore a fundamental fact that the carbon price fluctuations are complex, and so their conclusion may be inaccurate without distinguishing the specific market volatility states for revealing the impact of influential factors on the carbon price. Actually, different volatility states and trends imply different carbon price driving paths. Carbon prices exhibit completely different characteristics in high and low fluctuation states. In order to accurately characterise the price formation process, it is necessary to divide the carbon prices into high and low states separately (Zhang et al., 2019). Therefore, the core work of this article is studying the driving mechanism of carbon price in different market volatility states. Firstly, an autoregressive adjusted Markov mechanism transformation model is used to reveal the carbon price volatility state. Secondly, a multiple regression model is designed to test the relationship between carbon price and its influencing factors in high and low volatility states. We hope that this study can accurately capture the carbon price formation mechanism under different market states, so as to provide reference for investors to judge market situation and analyse carbon price trends.

METHODOLOGY

The research objective of this article is measuring the relationship between China carbon price and its influencing factors under different market volatility states. So, the first step is classifying the market volatility state of the carbon price, and then establishing a regression model between carbon price and its influencing factors.

Classifying the Carbon Price Volatility State Based on the MS(k)-AR(q) Model

As a type of financial time series, China carbon price has complex characteristics such as non-linearity, non-stationary and non-normality. For depicting these special characteristics, this article uses a Markov mechanism transformation model to classify the volatility state. Based on Hamilton's (1989) ideal, this article incorporates the carbon price autoregressive term into the model, and constructs an autoregressive adjusted Markov mechanism transformation model: MS (k)-AR (q), which is expressed as follows:

$$R_t = v(M_t) + \sum_{i=1}^{q} \phi_i(M_t) R_{t-1} + \varepsilon_t \tag{1}$$

Among them, R_t represents the carbon price series, $M \in \{1, 2, \ldots, k\}$ is a variable that describes the different market states, v is a time-dependent mechanism, and ϕ is a qth order auto-regressive coefficient. M_t follows a first-order Markov chain with a transition probability of $p_{ij} = P[M_t = j/M_{t-1} = i]$; which means the transition probability from the state i in time t–1 to the state j in time t. Note that $p_{i1} + p_{i2} + \ldots + p_{ik} = 1$. Actually, the transition probability matrix;

$$\begin{pmatrix} P_{11}, P_{21}, \ldots, P_{k1} \\ P_{12}, P_{22}, \ldots, P_{k2} \\ \vdots \\ P_{1k}, P_{2k}, \ldots, P_{kk} \end{pmatrix}$$

contains $k^2 - k$ parameters that controls the random behaviour of the state variable.

Furthermore, this article adopts Hamilton's maximum likelihood method for parameter estimation. Under the assumption that ε_t is normally distributed, the conditional probability of R_t when the state M_t takes the value of j is:

$$f(R_t \mid M_t = j, I_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma(j)}} \exp\left[\frac{-(R_t - v(j))^2}{2\sigma^2(j)}\right] \tag{2}$$

Among them, I_{t-1} denotes the observed values of all variables in state M_t up to time $t-1$, and θ represents the estimated parameter vector of the whole model.

Finally, the smoothing probability of carbon price state M_t is:

$$p(M_t = j \mid I_{t-1}; \theta) = \frac{P\left(\frac{j}{I_{t-1}}; \theta\right) f\left(\frac{R_t}{M_t} = j, I_{t-1}; \theta\right)}{f\left(\frac{R_t}{I_t}; \theta\right)} \tag{3}$$

Measuring The Relationship Between Carbon Price and Its Influential Factors

Based on the identified carbon price volatility states, this article constructs a multiple regression model to measure the relationship between carbon price and its influencing factors under the whole sample data, high volatility states, and low volatility state.

$$R_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon_{it} \tag{4}$$

where R_{it} represents the carbon price, X_1, X_2, X_n mean the inluencing actors o carbon price, β_0, β_1, β_2, β_n represent the regression coefficients, ε_{it} re presents th e residual.

EMPIRICAL ANALYSIS AND DISCUSSION

Sample and Its Descriptive Statistics

This article selects the Hubei emission allowances (HBEA) from the Hubei carbon emission exchange as the representative variable of China carbon price. Although China has launched carbon market trading pilot projects in Guangdong, Hubei, Shanghai, Shenzhen, Guangzhou and other regions since 2012, Hubei carbon market has a significant leading advantage in terms of market size, enterprises number, market maturity and price activity.

As for the carbon price influential factors, this article selects the JM future (JMF) from the Dalian futures exchange, oil futures (Oil) from the China financial futures exchange, China securities Index300 (CSI300) from the Shanghai Stock

Exchange, and European emission allowance future contract (EUAF) from the European carbon emission trading system. All the data are ranged from 2 January 2019 to 24 January 2024, with a total of 1,199 daily trading prices. Table 1 shows the basic descriptive statistics of carbon price and its influencing factors.

Table 1
Basic descriptive statistics of carbon price and its influencing factors

Statistical indication	HBEA	JMF	Oil	CSI300	EUAF
Mean	37.698	1747.802	72.644	4236.042	55.007
Median	38.680	1645.500	73.080	4034.510	56.870
Std. Dev.	8.590	527.183	20.065	580.740	26.694
Skewness	0.012	1.027	–0.018	0.434	0.013
Kurtosis	3.481	4.648	4.019	4.235	4.332
Jarque-Bera	115.169***	231.893***	0.085***	66.911***	139.057***
Observations	1,199	1,199	1,199	1,199	1,199

Note: *** means the significance in the level of 1%.

According to Table 1, firstly, the mean price of carbon price is 37.698, with a median of 38.68 and a skewness of 0.012. The mean and median carbon price are basically close, and the skewness is close to 0. This indicates that the probability density of China carbon price is basically symmetrical, there is no obvious left or right trailing phenomenon (as shown in Figure 1). The probability of outliers in carbon price series is relatively small. Secondly, in terms of kurtosis, compared with other influencing factors, the kurtosis of China carbon price is only 3.481, which is close to the standard state of a normal distribution kurtosis of 3, and also significantly lower than other market prices. This suggests that the signal trend of China carbon price is basically stable, the probability of extreme shocks is low. While we cannot ignore the risks of volatility clustering and price fluctuations in the long period of carbon price as shown in Figure 1. Thirdly, the Jarque-Bera (JB) statistics of China carbon price and its influencing factors are significant at the 1% level, indicating that we need to reject the null hypothesis of price series normally distributed, and accept the alternative hypothesis that all the price series are non-normal.

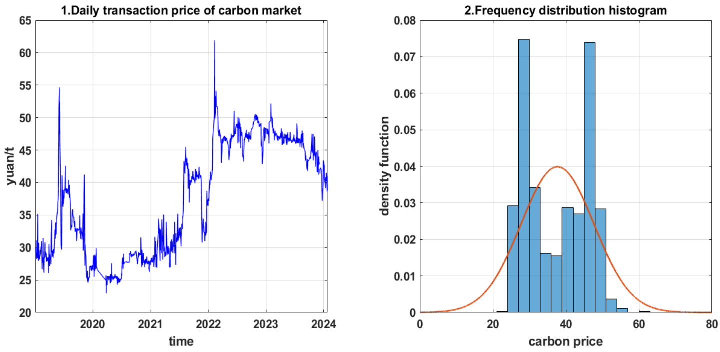

Figure 1: The daily carbon price and its distribution histogram

Classifying the Carbon Price Volatility States

This article uses an autoregressive adjusted Markov mechanism transformation model to classify the carbon market volatility states. During the experiment, we empirically measured the fitting performance of the Markov models when the states are 2, 3, 4, and the autoregressive orders are 2 and 3, respectively. Table 2 shows that when the preset state is 2, the autoregressive order is 2, the residual follows a normal distribution, the MS(2)-AR(2) model has the best fitting performance on China carbon price. That is the value of Akaike information criterion (AIC) and Bayesian information criterion (BIC) are 8.045 and 69.106, respectively, which are the minimum values among all the test models. Therefore, based on the AIC and BIC minimising principle, we use MS(2)-AR(2) model to classify the carbon market volatility state.

Table 2
The volatility state test result of China carbon price based on the MS(k)-AR(q) model

MS(k)-AR(q) model	Residual distribution	Number of parameters	Likelihood	AIC	BIC
MS(2)-AR(2)	**T**	14	–2893.815	12.059	83.297
	N	12	–2914.935	8.045	69.106
MS(2)-AR(3)	**T**	16	–2884.833	16.066	97.480
	N	14	–2907.988	12.050	83.287
MS(3)-AR(2)	**T**	24	–2852.912	32.088	154.210
	N	21	–2848.607	26.091	132.947
MS(3)-AR(3)	**T**	27	–2839.127	38.097	175.485
	N	24	–2839.356	32.097	154.219
MS(4)-AR(2)	**T**	36	–2828.724	56.105	239.288
	N	32	–2828.210	48.105	210.934
MS(4)-AR(3)	**T**	40	–2827.424	64.106	267.642
	N	36	–2825.074	56.107	239.290

After conducting the MS(2)-AR(2) model, we can obtain two carbon price volatility states as shown in Table 3. Firstly, the average volatility of state 1 is 1.463, with the autoregressive coefficients are –0.295 and –.087, which are significant at the 5% and 10% levels, respectively. The average volatility of state 2 is 6.354, with the autoregressive coefficients are –0.191 and –0.051, which are significant at the 5% and 10% levels, respectively. Secondly, the transition probabilities of state 1 and state 2 are 0.92 and 0.84, respectively, with the volatility duration periods are 12.49 and 6.34. This indicates that state 1 and state 2 are relatively stable and have strong persistence. The smoothing probabilities of the two states are shown in Figure 2.

Table 3
The state classification results of carbon price based on the MS(2)-AR(2) model

State	Average volatility (%)	AR(1)	AR(2)	Transition probabilities	State duration	State classification
State 1	1.463***	–0.295**	–0.087*	0.92	12.49	Low volatility
State 2	6.354***	–0.191**	–0.051*	0.84	6.34	High volatility

Note: ***, **, * means the significance in the level of 1%, 5% and 10%, respectively.

Thirdly, the volatility of state 2 is equivalent to 4.3 times of state 1. Therefore, this article considers state 1 and state 2 as the low volatility and high volatility respectively. Figure 2 shows the volatility of carbon price and its heterogeneity in low and high volatility state. Among them, we can clearly observe that the high volatility state not only has a high price volatility, but also has more sample points, and its price trend is obviously different from the low volatility state. So, it is necessary to test the carbon price driving mechanism based on the high volatility and low volatility state previously classified.

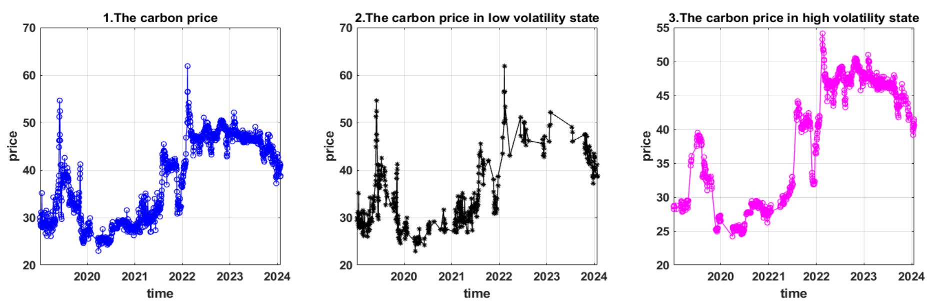

Figure 2: The carbon price trend on different market volatility state

Testing on the Carbon Price Influential Factors Based on Different Volatility States

According to previous analysis, it is found that the market changes and price trends of the China carbon price are quite complex, meaning the impact of influencing factors on carbon price also exhibit complex characteristics. Therefore, to reveal the relationship between carbon price and its influencing factors, it is necessary to grasp the carbon price driving mechanism under different market volatility states. The following test is based on the formula (4) depicted in subsection "Carbon price influencing factors test based on different volatility states".

Table 4
Basic regression results of carbon price and its influencing factors on the whole sample

Variable	Model 4_1	Model 4_2	Model 4_3	Model 4_4	Model 4_5
C	2.154*** (0.000)	0.524*** (0.000)	0.422*** (0.000)	0.500*** (0.000)	1.258*** (0.000)
HBEA(-1)	0.922*** (0.000)	0.986*** (0.000)	0.977*** (0.000)	0.959** (0.045)	0.943*** (0.000)
JMF	0.104*** (0.000)		0.105*** (0.000)		
Oil	0.027* (0.062)			0.015* (0.081)	
CSI300	0.224** (0.031)				
EUAF	0.216*** (0.000)				0.116*** (0.000)
R^2	0.974	0.973	0.974	0.974	0.974
AIC	3.489	3.517	3.512	3.503	3.494

Notes: ***, **, * means the significance in the level of 1%, 5% and 10%, respectively. Parentheses represent the *p*-value of regression results.

Carbon price influencing factors test based on whole sample

After using a multiple regression model to conduct on the whole sample data, the results as shown in Table 4 suggested that, firstly, the first-order lag term of carbon price is significant at the 1% level, and the estimated influence coefficient is positive. This means that the carbon price has obvious memory characteristics, the historical carbon price has a positive impact on the current price. Studying the history carbon price has a strong guiding significance for judging the current price. This finding is completely consistent with the study of Yun et al. (2023) that carbon price has short-term memory characteristics, and it is useful to forecast carbon price accurately after incorporating the lag term of carbon price into the forecasting models.

Secondly, the regression coefficients of JMF and Oil are significantly positively, and the estimated influence coefficient are 0.104 and 0.105 in model 4_1 and model 4_3, respectively, both significant at the 1% level. The estimated influence coefficients of Oil are 0.027 and 0.015 in model 4_1 and model 4_4, respectively, both significant at the 10% level. This indicates that the price rising of JMF and Oil will promote the carbon price. In fact, the coal and crude oil are both fossil fuels. When the fossil fuel price is rising, manufacturing industrial enterprises will face higher production costs, and the substitutes demand will be increasing according to economic laws. So, the carbon price will be increasing with the significant carbon allowance demand, as a result, a positive relationship between fossil energy prices and carbon price can be obtained. Those conclusions have also been detected in the studies of Tsai et al. (2024) and Maneejuk et al. (2024) that the international energy prices are basically consistent with changes in carbon prices, and the policies that affect energy prices will ultimately have an impact on carbon prices.

Thirdly, the carbon price is significantly positively correlated with the macroeconomic indicator CSI300, with an influence coefficient of 0.224, which is significant at the 5% level. CSI300 is a representative indicator of China macroeconomic. When the macroeconomic indicator is increasing, the strong social demand will drive various manufacturing industries to increase their carbon allowance consumption, so as to improve the carbon price. Conversely, when the macroeconomic indicator is declining, the production expectation of industrial enterprises is weak, as a result, the carbon price will be declining as the carbon allowance demand decreases.

Fourthly, there is a significant positive correlation between China carbon price and European carbon price. Specifically, the estimated influence coefficients of the European carbon price EUAF in model 4_1 and model 4_5 are 0.216 and 0.116, respectively, both significant at the 1% level. Although there are still obvious differences between the China and European carbon market in market size, mechanism construction, marketisation level, both are trading carbon allowance to promote the low-cost pollutant reduction mechanisms. So, the changes in European carbon price are basically consistent with those in China, the rising in European carbon price will also improve the China carbon price.

Carbon price influencing factors test based on different volatility states

The high volatility state indicates the carbon price change frequency and magnitude are high, there are systemic risks hidden in the market, the price uncertainty is more obvious. For investors, high volatility state means high loss risks, and investors are tend to engage in cross market investment for controlling the market risks. While, the low volatility state means the carbon market is in a stable equilibrium state that with low risk and little market change. In this state, market fundamentals have a significant impact on carbon price, and the lack of arbitrage space makes it difficult to encourage investors to take cross market arbitrage. Table 5 shows the basic regression results of carbon price and its influencing factors on high volatility state.

Table 5
Basic regression results of carbon price and its influencing factors on high volatility state

Variable	Model 4_1	Model 4_2	Model 4_3	Model 4_4	Model 4_5
C	4.009*** (0.003)	2.073*** (0.002)	1.392** (0.031)	1.349** (0.039)	3.051*** (0.000)
HBEA(-1)	0.838*** (0.000)	0.94*** (0.000)	0.895*** (0.000)	0.886*** (0.000)	0.873*** (0.000)
JMF	0.001 (0.154)		0.001 (0.204)		
Oil	0.015 (0.256)			0.039 (0.104)	
CSI300	0.006* (0.062)				
EUAF	0.020*** (0.008)				0.031*** (0.09)
R^2	0.891	0.884	0.888	0.887	0.889
AIC	4.639	4.676	4.649	4.651	4.641

Notes: ***, **, * means the significance in the level of 1%, 5% and 10%, respectively. Parentheses represent the *P*-value of regression results.

The results shown in Table 5 suggested that, firstly, whether the market is in a high volatility state or a low volatility state, the carbon price lag performance is still obvious. That is, the carbon price has a significant positive long-term memory characteristics. For example, when the carbon price is in a high volatility state, the first-order lag coefficients of carbon price are 0.838, 0.94, 0.895, 0.886 and 0.873, in model 4_1, model 4_2, model 4_3, model 4_4 and model 4_5, respectively, all of the variables are significant at the 1% level. Similarly, when the carbon price is in a low volatility state, the first-order lag coefficients are 0.948, 0.993, 0.988, 0.974 and 0.961, in model 4_1, model 4_2, model 4_3, model 4_4 and model 4_5, respectively, and all of the variables are significant at the 1% level.

Secondly, in high volatility state as shown in Table 5, the carbon price is only significantly positively correlated with macroeconomic variable CSI300 and the European carbon price EUAF, while there is no significant correlation with other influencing factors. High market volatility state means the carbon market faces significant risks. For risk management considerations, investors in other influencing factor markets usually avoid investing in the carbon market. That is, carbon market investors are prone to choose macroeconomic fundamentals and similar market EUAF as hedging tools when facing high risks. So, the carbon price is positively correlated with macroeconomic indicators and European carbon price.

Table 6

Basic regression results of carbon price and its influencing factors on low volatility state

Variable	Model 4_1	Model 4_2	Model 4_3	Model 4_4	Model 4_5
C	1.116**	0.280***	0.225***	0.329**	0.833***
	(0.028)	(0.000)	(0.000)	(0.034)	(0.000)
HBEA(-1)	0.948***	0.993***	0.988**	0.974***	0.961***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JMF	0.001*		0.005*		
	(0.064)		(0.058)		
Oil	0.059*			0.009*	
	(0.091)			(0.053)	
CSI300	0.001***				
	(0.002)				
EUAF	0.011***				0.012***
	(0.000)				(0.000)
R^2	0.974	0.988	0.988	0.988	0.988
AIC	3.489	2.765	2.763	2.754	2.746

Notes: ***,* *, * means the significance in the level of 1%, 5% and 10%, respectively. Parentheses represent the *P*-value of regression results.

Thirdly, in low volatility state as shown in Table 6, there is a significant positive correlation between carbon price and all influencing factors, this conclusion is consistent with previous findings. For example, the estimate influence coefficients of JMF are 0.001 and 0.005 in model 4_1 and model 4_3, respectively, both significant at the 10% level. The estimate influence coefficients of Oil are 0.059 and 0.009 in model 4_1 and model 4_4, respectively, both significant at the 10% level. Furthermore, the carbon price is significantly positively correlated with the macroeconomic indicator CSI300, with an estimate influence coefficients is 0.001, which is significant at the 1% level. The estimate influence coefficients of carbon price with the European carbon price EUAF in model 4_1 and model 4_5 are 0.011 and 0.012, respectively, both significant at the 1% level.

Finally, it is worth noting that, although the relationship between carbon price and its influencing factors in low volatility state is basically consistent with the general regression results proposed in subsection "Carbon price influencing factors test based on whole sample", the regression coefficients in low volatility state are significantly smaller than those of the general regression. Those findings indicate that under the shock of smaller market risks, the impact of various influencing factors on carbon price is relatively small, the driving force of carbon price is relatively weak. While the driving force may be enhanced as the increasing of market risks. The possible reason is that low volatility means low risk, and high volatility reflects high risk. Driven by chasing profit, investors tend to allocate cross market funds in high volatility market state, resulting in stronger driving force of the carbon price.

CONCLUSION

With the increasing attention on global climate issues, China, as one of the world's largest greenhouse gas emitters, is facing series environmental pressure. In this background, to address the constraints of environmental issues on sustainable economic growth, the Chinese government officially implemented the carbon peak and carbon neutrality strategy in September 2020. As a market-oriented mechanism for implementing the proposed strategy, accelerating the carbon market construction has become a specific measure to achieve the emission reduction goals. The carbon market plays an actively role in helping China reduce the carbon emissions. The higher the market operation efficiency, the more significant performance of emissions reduction. Therefore, studying the price formation and determination mechanism of the carbon market, explaining the transmission path of carbon premium are the keys to promote the carbon emission reduction and achieve the target of carbon peak and carbon neutrality. This article focuses on the special characteristics of the carbon market, conducts multiple regression model on different carbon price volatility states, and reveals the driving mechanism of carbon price. That is, an autoregressive adjusted Markov mechanism transformation model is used to classify the carbon price states. In addition, a multiple regression model is conducted to test the influential path of carbon price formation in different states. The major conclusions are as follows:

Firstly, the autoregressive adjusted Markov model MS(2)-AR(2) can effectively fit the complex China carbon price, the price can be classified into low volatility state and high volatility state with the average volatility of 1.463 and 6.354, respectively. Secondly, in high volatility state, the carbon price is only positively influenced by macroeconomic factors CSI300 and similar carbon price EUAF, while in low volatility state, carbon price is significantly positively influenced by energy market products of JMF and Oil, macroeconomic factors CSI300 and similar carbon price EUAF. However, this impact is significantly weaker than the general regression results in a higher market risk. This evidence shows that compared with low market risk state, the high market state can bring more risk premium for investors. Driven by chasing profit, investors tend to take on some systemic risks for obtaining potential excess returns, resulting in more factors driving the carbon price formation in high volatility state.

DISCLOSURE STATEMENT

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