Empirical Study and Prediction on the Influencing Factors of Carbon Emission Rights Trading Prices-Taking the National Carbon Emission Rights Trading Market in China as an Example

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Abstract. Under the backdrop of global climate change, market-based emission reduction has become a consensus. This paper takes the national carbon market from 2021 to 2025 as the object of study, selects variables such as policies, EUA prices of the European Union, Gross Domestic Product (GDP), HS300, coal prices, and international oil prices, and unifies daily and quarterly data into monthly data for OLS regression analysis. The research findings indicate that policies and energy prices are the core influencing factors of carbon prices: lenient policies (such as a slight increase in quotas and the restart of CCER) and a decline in energy prices will lower carbon prices, while an increase in crude oil prices will push carbon prices up. The EUA price in the European Union has an overflow effect. At the same time, the research has successfully solved the problem of integrating multi-frequency data, verified the rationality of energy price indicators, and the constructed model can predict the trend of carbon prices in the next month. This research fills the empirical gap in the national carbon market, provides quantitative basis for market stability and mechanism improvement, and helps to achieve the "dual carbon" goals.

Keywords: Carbon Emission Rights Market, Carbon Trading, Carbon Price Regulation and Prediction.

1. Introduction

The ecological crisis triggered by global climate change has become a governance challenge faced by all countries. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) clearly states that human activities since industrialization have been the dominant factor in global warming, with carbon dioxide accounting for as much as 77% of total greenhouse gas emissions. To address this challenge, market-based emission reduction tools have become a global consensus. The Paris Agreement has established a unified global carbon reduction framework, with 178 countries having signed it by 2018. The European Union has formed a mature carbon pricing mechanism through the "Carbon Border Adjustment Mechanism" and the EU Emissions Trading System (EUETS), setting a benchmark for the development of the global carbon market [1]. Holding the position of the world's foremost greenhouse gas emitter and primary energy consumer, China is actively implementing the "dual carbon" goals (carbon peaking and carbon neutrality), and the construction of its carbon market is gradually moving towards standardization. On July 16, 2021, the national carbon emissions trading market was officially launched, marking the transition of China's carbon market from regional pilot to a unified national stage. With its first phase comprising 2,162 power industry enterprises and covering around 4.5 billion tons of carbon dioxide emissions, it became the world's largest carbon trading market. The stability of its price mechanism directly determines the impetus for enterprises to reduce emissions, the efficiency of government policies, and the progress of green transformation [2].

The carbon emission trading price (referred to as "carbon price") is the core of resource allocation in the carbon market, and its fluctuations are subject to a complex array of influencing factors. Existing research indicates that macroeconomics, energy prices, policy adjustments, climatic factors, and cross-market spillover effects all significantly impact the carbon price. The study by Ma et al. revealed a converse impact of macroeconomic and energy price factors versus the air quality index on carbon prices, with the former exerting a negative influence and the latter a positive correlation [3]. Liao et al. pointed out that there is a significant correlation between electricity prices, historical prices, and carbon prices [4]. Other scholars have also verified the bidirectional causal relationship between economic policy uncertainty and carbon prices [5].

Scholars have developed three primary types of forecasting methods to understand the price dynamics in the carbon market. The first is traditional statistical models, such as the Autoregressive Integrated Moving Average model (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity model (GARCH), which can depict linear patterns but are difficult to adapt to the inherent non-linearity and non-stationarity characteristics of carbon prices, resulting in significant long-term prediction errors. The second is machine learning models, including Random Forest (RF), Backpropagation (BP) neural networks, etc. Zheng and Deng pioneered the integration of sentiment analysis with Random Forest and SHAP models, creating a multidimensional framework that elucidates carbon price variations across China's eight pilot ETS programs [1]. Wang et al. fully integrated PSO and GA to enhance the traditional BP neural network. This method is different from previous studies that specifically used PSO-BP or GA-BP neural network models to predict carbon prices. This method not only solves the common local optimal problem in previous technologies, but also helps to achieve more accurate and reliable carbon price predictions [6]. The third is deep learning and hybrid models, such as the application of convolutional neural networks and long short-term memory networks (CNN-LSTM) models with historical time series and multi-indicator features, and the combination of empirical mode decomposition-genetic algorithm-error backpropagation algorithm (EEMD-GA-BP) algorithm to solve the problem of mode aliasing, the spatio-temporal multi-dimensional collaborative attention network (TSMA) to capture regional carbon price correlations, for example, Chen et.al. used convolutional neural networks and long short-term memory networks (CNN-LSTM) models, analyzed a single historical time series and multi-indicator features, thereby enhancing the comprehensiveness and accuracy of the prediction [7, 8].

Although these methods have achieved some breakthroughs in terms of accuracy, some significant gaps still existed in the research on the national carbon market in China. Firstly, there is a notable scarcity of empirical studies focusing on the national carbon market. Existing studies mostly focus on the EU ETS or local pilot projects in China, paying less attention to the unified national market that was launched in 2021. Moreover, they do not fully incorporate the characteristic of the national market where the "electric power industry leads and gradually expands" and thus are unable to reflect the driving mechanism of carbon prices at the national level [9]. Secondly, the problem of integrating multi-frequency data has not been solved. Carbon price data is mostly in the form of daily high-frequency data (such as the daily comprehensive price of the national carbon market), while macroeconomic indicators such as GDP growth rates are mostly in the form of quarterly or annual low-frequency data. Existing studies either ignore low-frequency variables or simply interpolate, failing to verify the impact of data frequency adaptation on model accuracy; at the same time, there is no unified standard for quantifying policy documents (such as emission reduction targets, quota adjustments) and climate factors, and how to integrate such qualitative or low-frequency data with high-frequency carbon price data has become a key obstacle in empirical analysis [10, 11]. Thirdly, the rationality of the selection of energy price indicators lacks verification. Most existing studies simply use "energy price" as the explanatory variable without specifically addressing China's energy structure characterized by "abundant coal, scarce oil, and insufficient gas". They fail to verify the correlation between specific indicators (such as Caofeidian Index, China's crude oil comprehensive landed price index) and the national carbon price, which may lead to deviations in the depiction of the transmission mechanism between the variables and the carbon price.

Against this backdrop, this paper centers on China's national carbon emission trading market, analyzing data from the post-launch period of 2021 to 2025. It conducts research on three core issues: "Identification of factors influencing carbon price - Integration of multi-frequency data - Construction of prediction models". The specific goals include identifying the core factors influencing the national carbon price, clarifying the direction and intensity of the effects of variables such as policy regulation, energy prices, and the macroeconomy; solving the problem of integrating multi-frequency data (daily carbon prices, quarterly GDP, annual climate data) and quantitative variables (policy data) into models, verifying the rationality of energy price indicators; constructing empirical regression models and prediction models applicable to the national carbon market, providing references for market participants' decision-making and policy optimization.

The research value of this paper lies in two aspects. Theoretically, it fills the gap in the empirical research of the national carbon market, explores the integration methods of multiple frequency and multiple type data, and enriches the research framework of determinants of Carbon Pricing. This study employs an OLS regression model to analyze a set of selected factors within the carbon emission market. The analysis provides an empirical foundation for stabilizing the national carbon market price and improving its mechanism, thereby contributing to the realization of the "dual carbon" goals.

2. Model Design

In this paper, the carbon emission allowance trading price (CEA) serves as the dependent variable. It is represented by the daily closing price of the national carbon market's composite quote, with the data spanning from July 19, 2021, to July 31, 2025, as provided by the Wind database. Since the original data is at the daily level, the original data is averaged by month to obtain the monthly carbon emission rights trading price.

This paper selects the China Economic Policy Uncertainty Index (CN_EPU), the EU Carbon Futures Price (EUA), and China's Quarterly GDP (CN_GDP) as explanatory variables. Among them, the China Economic Policy Uncertainty Index (CN_EPU) can reflect the impact brought about by fluctuations in China's policies [12]; This paper selects the closing price of the EU Carbon Futures Price (EUA) for each trading day during the period from July 19, 2021 to July 31, 2025 as the indicator to measure the EU Carbon Futures Price (EUA). Since the original data is daily data, the original data is averaged by month to obtain the monthly foreign carbon emission rights trading price; The data is averaged by month to obtain the monthly carbon emission rights trading price. In this paper, China's quarterly GDP (CN_GDP) serves as the benchmark indicator for the nation's economic standing. The data coverage extends from the third quarter of 2021 to the second quarter of 2025. The data is sourced from the National Bureau of Statistics. Since the original data is in quarterly format, interpolation methods were used to expand the quarterly data into monthly data to unify the frequency.

This paper selects the Shanghai-Shenzhen 300 Index (HS300), domestic coal prices (CN_COAL), and international oil prices (OIL) as control variables (Controls). These three control variables respectively reflect the trends of China's financial market, domestic energy, and international energy to a certain extent. The data sources are official databases such as the Wind database.

The specific model is set as

$$\mathrm{CEA} = \alpha + \beta_2 \mathrm{CN\_EPU} + \beta_3 \mathrm{EUA} + \beta_4 \mathrm{CN\_GDP} + \mathrm{CONTROLS} + \mathrm{u}_0 \quad (1)$$

The model is specified as follows: α is the constant term. The coefficients β_2, β_3 and β_4 correspond to the explanatory variables, reflecting the magnitude and direction of each factor's influence on the dependent variable. Finally, is the random error term, which encompasses the net effect of all relevant but excluded variables and any potential measurement errors in the data.

3. Empirical Results

3.1. Descriptive Statistics

Statistical tests were conducted on each variable, resulting in Figure 1. As shown in Figure 1, the internal data of each variable fluctuated significantly and did not distribute uniformly. However, by comparing their respective means and medians, it can be found that the means of CEA, CN_EPU, and OIL are all greater than their medians, indicating a right-skewed data distribution, with some data values being relatively large, pulling up the average value; the mean of CN_COAL is less than its median, indicating a left-skewed data distribution, with some data values being relatively small, pulling down the average value; the means of EUA, CN_GDP, and HS300 are relatively close to their medians, indicating a roughly symmetrical data distribution.

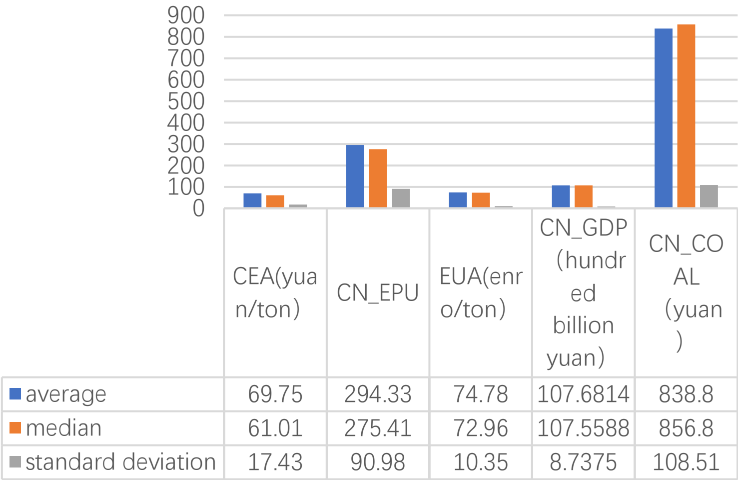

Figure 1. The mean, median and standard deviation of each data set.

3.2. Regression Analysis

A regression analysis was conducted on the existing data, and the following results were obtained.

Table 1. Parameter estimation results.

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	65.7583	63.37322	1.037635	0.3102
X2 (CN_EPU)	-0.03732	0.030646	-1.21787	0.2356
X3 (EUA)	-0.86554	0.239614	-3.61223	0.0015
X4 (GDP)	0.000814	0.000265	3.067063	0.0055
X5 (HS300)	-0.00445	0.005469	-0.81346	0.4243
X6 (CN_COAL)	-0.07204	0.031348	-2.29802	0.031
X7 (OIL)	0.949262	0.526668	1.802394	0.0846
R-squared	0.66595		Mean dependent var	78.60267
Adjusted R-squared	0.578807		S.D.dependent var	16.25714
S.E.of regression	10.55079		Akaike info criterion	7.751241
Sum squared resid	2560.339		Schwarzcriterion	8.078187
Log likelihood	-109.269		Hannan-Quinn criter.	7.855834
F-statistic	7.641999		Durbin-Watson stat	0.731445
Prob (F-statistic)	0.000135			

As shown in Table 1, in terms of goodness of fit, the model has a good fit for the sample, and the overall linear relationship of the equation is significant. In the t-test, at the significance level α=0.05, the explanatory variables X3, X4, and X6" have significant effects on the explained variable (Y). Additionally, at the significance level α=0.10, X2" and X5" have no significant effect on Y.

3.3. Test for Multicollinearity

The correlation matrix for the independent variables (Table 2) shows no highly correlated pairs of explanatory variables, which suggests that the model does not suffer from serious multicollinearity.

Table 2. Coefficient matrix of independent.

Variables	X2	X3	X4	X5	X6	X7
X2	1	-0.11597	0.053766	0.135188	-0.63286	-0.68407
X3	-0.11597	1	-0.06427	0.233671	0.16301	0.358689
X4	0.053766	-0.06427	1	-0.43643	-0.26973	-0.27585
X5	0.135188	0.233671	-0.43643	1	0.11809	-0.06765
X6	-0.63286	0.16301	-0.26973	0.11809	1	0.741643
X7	-0.68407	0.358689	-0.27585	-0.06765	0.741643	1

4. Suggestions

The research results indicate that effective governance of the carbon emission trading price hinges on anchoring the core influencing factors to establish a precise regulatory mechanism, one that is directly informed by empirical evidence. In response to the significant influence of domestic coal prices and international crude oil prices on CEA, it is suggested to establish a "coal-crude oil-carbon price" linkage monitoring mechanism. On one hand, through medium- and long-term contracts for coal and reserve regulation, domestic coal prices can be stabilized to avoid a sharp decline that would cause excessive pressure on CEA; on the other hand, strengthen the early warning of international crude oil prices, combined with China's energy import structure, through crude oil reserve release and the substitution of new to cushion the carbon market against disruptive price fluctuations. At the same time, increase support for clean energy policies, increase the proportion of wind power and photovoltaic in energy consumption, and fundamentally weaken the excessive influence of traditional energy on the carbon price.

Realize the dynamic matching between macroeconomy and carbon quotas. Based on the positive correlation between China's quarterly GDP and CEA, it is suggested to incorporate the GDP growth rate as a dynamic adjustment factor for the allocation of carbon quotas. When the GDP growth rate exceeds expectations (such as exceeding 5%), some reserved quotas should be released in advance to alleviate the demand pressure; when the GDP growth rate slows down, the quota issuance should be appropriately tightened to prevent the CEA from falling excessively due to insufficient demand. This measure can ensure that the carbon price remains relatively stable throughout the economic cycle and maintains the motivation for enterprises to reduce emissions.

Establish an international carbon market risk early warning system. In response to the negative impact of the EU carbon futures price (EUA) on CEA, it is suggested to establish a regular monitoring mechanism for the EU carbon market. Analyze the transmission path of EUA price fluctuations to the domestic market and formulate cross-market risk response plans. For example, set a threshold for CEA fluctuations, and activate temporary adjustment measures when the threshold is triggered to avoid abnormal fluctuations in international carbon prices causing market fluctuations in the domestic market, and ensure the stability of the national carbon market operation.

The focus is on establishing a multi-dimensional risk prevention and control market guarantee system. To cope with the risk of carbon price fluctuations, it is suggested to set up a three-level carbon price warning line of "yellow - orange - red". When the monthly fluctuation of CEA exceeds 10% (yellow warning), the market liquidity monitoring will be initiated; when it exceeds 15% (orange warning), the supply and demand will be adjusted by increasing or reducing quotas through market makers; when it exceeds 20% (red warning), some high-frequency trading will be suspended. With the increasing participation of financial institutions in the carbon market, it is imperative to establish a risk isolation mechanism. This is crucial for insulating the market from spillover effects of macro-policies and external shocks, thereby safeguarding its healthy and stable operation [13].

Ensuring data integrity and transparency is fundamental to the healthy functioning and credibility of the carbon market. In terms of the issues such as the lack of data in the Caofeidian Index in the empirical study, it is suggested that the National Bureau of Statistics and the China Electricity Industry Federation take the lead in establishing a "National Carbon Market Core Indicator Database", unifying the statistical standards and release frequencies of data such as energy prices, industry GDP, and policy documents, to reduce the impact of data absence on model accuracy. At the same time, regular carbon price operation reports should be released, disclosing the monthly changes in core influencing factors, to enhance market transparency; regularly input new data into the model for parameter iteration, drawing on the ideas of multi-factor integration and nonlinear analysis, and gradually introducing machine learning methods (such as random forests, XGBoost) to optimize the prediction algorithm, to improve long-term prediction accuracy.

5. Conclusion

This article is based on monthly data from July 19, 2021 to July 31, 2025 (obtained by averaging the daily closing prices). The national carbon emission trading price (CEA) shows the characteristics of "median stability, range fluctuation, and multi-factor interaction". At the numerical level, the mean of CEA is 69.75 yuan/ton, and the median is 61.01 yuan/ton. The mean being higher than the median indicates a slightly right-skewed distribution of prices, and a few high-priced trading days (with the maximum value of 104.49 yuan/ton) have pushed up the overall mean. The price range spans 61.69 yuan/ton (minimum value 42.80 yuan/ton), with a standard deviation of 17.43, indicating that the carbon price has some fluctuations but has not shown extreme anomalies. This is in line with the operational pattern during the market cultivation period. At the correlation level, the fluctuations of CEA are highly correlated with the macroeconomy and the energy market. As China's quarterly Gross Domestic Product (GDP) increased from 8.99 trillion yuan to 12.56 trillion yuan, the carbon price showed a gradual upward trend, reflecting the transmission logic of "economic recovery - increased power demand - rising carbon quota demand". The fluctuations in domestic coal prices (average 838.80 yuan) and international crude oil prices (average 83.33 US dollars per barrel) also exerted a phased pull-on CEA, confirming the multi-factor driving nature of the national carbon price.

The constructed "multi-frequency data integration + OLS regression + generalized difference correction" prediction model has a good fitting effect. The adjusted R^2 is 0.5788, which can explain approximately 57.9% of the CEA fluctuations. The F statistic is 7.642 and the P value is 0.000135 (1% significant), indicating that the overall linear relationship of the model is significant and can effectively capture the patterns of carbon price changes. This model solves the problem of multi-frequency data adaptation in traditional research, such as converting quarterly GDP through interpolation into monthly data and taking the monthly average of daily energy prices. It also addresses the issue of missing data for the Caofeidian index from July 2021 to April 2023 by aligning the data to ensure the validity of the regression.

In this paper, the model also has limitations, which are as follows. Firstly, the OLS method was used for regression analysis in this paper, which has the problem of linear dependence. The model is unable to capture the non-linear characteristics of the carbon price, and the long-term prediction accuracy is limited. Moreover, it fails to meet the requirements for daily and weekly high-frequency predictions. Secondly, there are deficiencies in the variable dimension. For instance, directly using the China Economic Policy Uncertainty Index as a policy variable leads to the failure to subdivide policy types such as environmental protection and energy, and the lack of in-depth analysis of cross-market transmission paths. Thirdly, the quantification of low-frequency and qualitative variables is insufficient. Issues such as the unverified GDP interpolation method and the inability to explain 42.1% of the carbon price fluctuations exist.

In response to these limitations, this paper presents the following outlooks. Firstly, in terms of the model, the GARCH-MIDAS hybrid model is introduced to enhance the utilization of high-frequency data, and machine learning (RF) / deep learning (CNN-LSTM) is combined to capture nonlinear features; Secondly, in terms of variables, policy types can be subdivided, the transmission path of the international carbon market can be analyzed, and the carbon price driving factors after industry expansion (steel, cement) can be included; Finally, in terms of data, the accuracy of interpolation methods is compared, the handling of missing values is optimized (such as multiple interpolation), and other variables such as weather variables are introduced to further explain the changes in carbon prices.

AuthorS Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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