

# The impact of China's entry into the carbon trading market on European carbon prices

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**Abstract.** As the world's largest greenhouse gas emission country, the success or failure of the Chinese national carbon emissions trading market will largely determine climate change's further development. Chinese national carbon market, which was opened on July 16, 2021, will also exert spillover effects on carbon trading markets in other countries, including the European carbon emissions trading market, which will have a more significant impact. This paper uses the double difference model(DID), sets the price of European certification emission reduction(CER) as the dependent variable, and takes China's entering into the carbon emissions trading market and the RMB exchange rate as the independent variable to test the influences of China's entering in the carbon emissions trading market on the European CER price. After that, non-linear machine learning models such as support vector machines are used to fit and predict the price of European CER, which further verifies that the opening of the Chinese national carbon emissions trading market contributes to a decline in European CER price.

**Keywords:** carbon emissions trading system; European carbon financial market; DID; Support Vector Machine; RMB exchange rate.

## 1. Introduction

To deal with climate change caused by greenhouse gas emissions, China launched a quota framework for the carbon emission market in 2011. From 2013 to now, China has launched seven pilot carbon emission quota trading markets in Tianjin, Shanghai, Shenzhen, Beijing, Guangdong, Hubei, and Chongqing to ensure a smooth realization of the global carbon emission reduction target. Nowadays, the pilot carbon emissions trading market in China has been developing continuously, and the relevant market systems have become more and more perfect, showing a stable and positive situation as a whole, to lay a good institutional and data foundation for building a national market for carbon emissions trading, and for the follow-up experience of the national carbon market. Summarizing the experience and lessons of the national carbon emissions trading market, the Chinese national carbon emissions trading market was fully launched on July 16, 2021.

It is worth noting that the emergence of a Chinese carbon market may cause price fluctuations in the European carbon emissions trading market. The European carbon emissions trading market will be influenced by the macro-economy, financial market, and energy market. Since the establishment of the Chinese carbon emissions trading market, carbon prices have fluctuated greatly, and the transaction volume will also fluctuate frequently with changes in government policies. In the eight carbon pilot cities in China, the transaction volume is 0, and the price of CER has fallen seriously, which hardly benefits the smooth operation of the carbon emissions trading market. What's more, the Chinese carbon emissions trading market was established relatively late, and its theoretical research and practical development are far behind the foreign carbon emissions trading market, for example, the EU Carbon Emission Trading System. What's more, there are big differences in the trading mechanism, carbon price level, and market activity among the eight carbon pilot cities in China, which is not advantageous for the establishment of a centralized national carbon market. The problems mentioned above require more scholars to pay attention to the research on the carbon emissions trading market. Therefore, exploring the most significant factors of the price of CER in Europe is of profound significance for improving the theoretical system, laying a solid foundation for the development of the national carbon emissions trading market of China, and pushing the establishment of a centralized national carbon emissions trading market.

Foreign carbon emissions trading markets were established earlier, and various mechanisms are relatively complete, so there is abundant research on the formation mechanism of CER's prices. Through empirical analysis, Mansanet et al. found that the average temperature exerted no important effect on EUA prices, but the fluctuation range of temperature deviation from the chief value was positively correlated with EUA prices [1]. Piia Aatola et al. believed that the influence of carbon price on electricity price is positive and unbalanced [2]. Marc et al. used the copula model to compare EUA prices with commodity price trends and macroeconomic development and finally concluded that EUA futures prices are positively correlated with coal, electricity, natural gas futures prices, and energy spot prices [3]. During the financial crisis, especially the economic recession, the EUA futures price yield has an intense correlation with the macroeconomic market. Christianset et al. believe that the trend of a carbon price is formed by the combined effect of energy prices, weather conditions, emission reduction policies of relevant governments and authorities, psychological expectations of carbon market traders, and even market conditions [4].

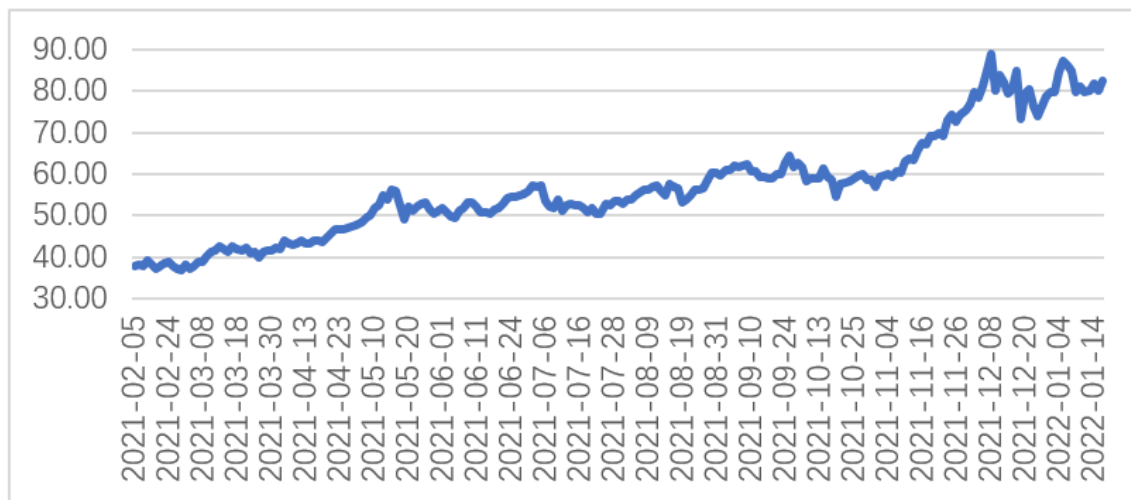
Domestic research on the factors affecting the price of CER is in its infancy. Tao Chunhua found that there is a strong negative connection between the stock market returns of high-carbon emission industries and the market price of carbon emission rights in Shanghai by examining the linkage between Chinese carbon emissions trading and the stock returns of sample industries, and the two have long-term mutual effects [5]. Chen Xiaohong et al. used panel regression and AR (1)-GARCH (1,1) model analysis methods to analyze the trading price and related influencing factors of carbon emission rights on the Chicago Climate Exchange [6]. Ding Yang took the Shenzhen carbon allowance price in China as an example to analyze the significant factors of the domestic price of carbon and used the GEN method for variable selection and parameter estimation. [7]

Analyzing and sorting out the research of domestic and foreign scholars, it can be found that: from the perspective of research objects, most of the existing research is oriented towards a single study on the EU carbon market, and a few studies considering the Chinese carbon emissions trading market and the European carbon emissions trading market at the same time. From the perspective of research methods, the current studies mainly analyze macro-policy and other aspects, or select models for static analysis, but cannot analyze the interaction between variables from a dynamic level. Therefore, this paper uses the DID model to dig deeper into the impact mechanism of China's entry into the carbon emissions trading market on the European CER's price and concludes that China's entry into the carbon emissions trading market and the devaluation of the RMB exchange rate contributes to a decline in European CER price. Subsequently, the neural network model is used to fit and forecast the European price of CER. The fitting results further test the influences of China's entry into the carbon emissions trading market and the exchange rate of RMB on the European price of CER.

On the one hand, studying the vital factors and influencing mechanisms of European price of CER can provide theoretical guidance for the formulation and adjustment of prices of CER in China, help the government determine the supply of CER and the method of allowances, and ensure the stability of prices of CER and the smooth operation of Chinese carbon emissions trading market, reduce market risks, narrow the gap between various carbon pilot markets, promote the founding of a centralized national carbon financial market, expand carbon emission reductions, and accelerate the realization of carbon peak carbon neutrality goals. On the other hand, the research also provides market information to emission companies and other investors, improves emission reduction efficiency of emission control companies, reduces emission reduction costs, helps carbon market investors to reasonably predict the future trend of CER prices, builds a risk early warning mechanism, masters the initiative in decision-making, and avoids extreme investment behavior, thereby ensuring the smooth functioning of the market.

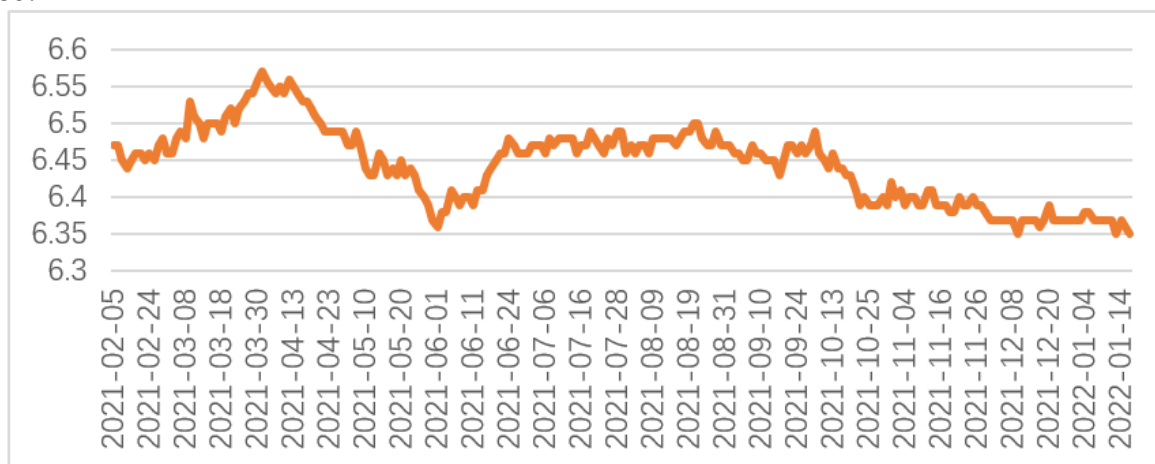
The text structure for the rest of this article is as follows. The second part makes a preliminary analysis of the data used in the paper, the third part introduces the research methods used in this paper, which are the DID model and the machine learning model, the fourth part analyzes the results of the research, while the final part summarizes the entire article.

## 2. Data



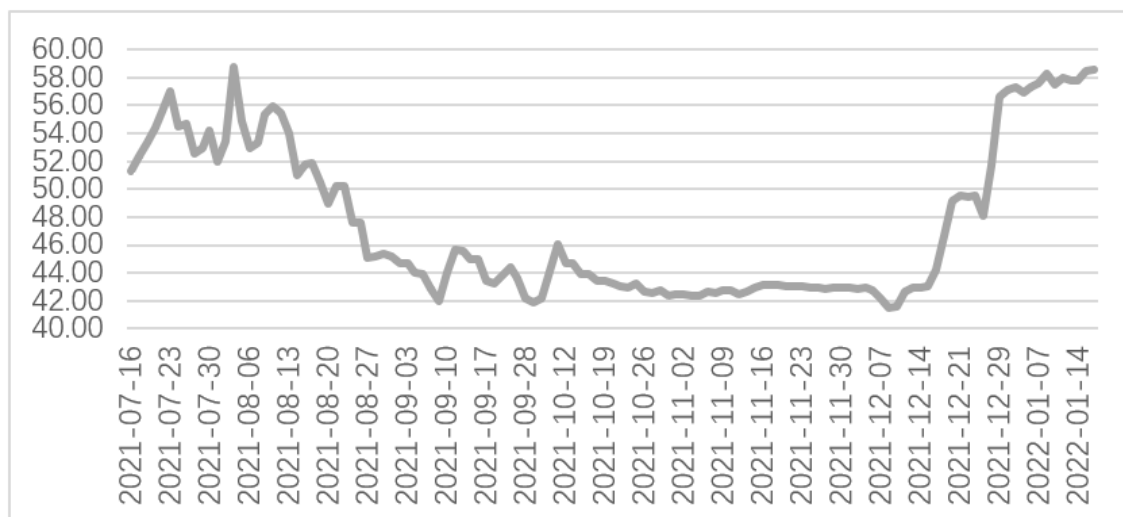
**Fig. 1** Spot settlement price of EU CER

According to Fig.1, from the tendency of the spot settlement price of EU carbon allowances in the figure, it can be seen that the European carbon price has a steady increase to 52.58 euros per ton from March 6, 2021, to May 20, 2021, and has been in a volatile upward trend until October 20, 2021, to 57.76 euros per ton. After that, between October 20, 2021, and December 10, 2021, the European carbon price showed a rapid upward trend, with a maximum value of 87.15 euros per ton during the period.



**Fig. 2** The exchange rate of RMB to USD

According to Fig.2, from the trend of the exchange rate of RMB to USD in the figure, it can be seen that the exchange rate of RMB began to drop rapidly to 6.44 on May 24, 2021, after rising to 6.57 on February 5, 2021, to March 31, 2021. From May 24, 2021, to June 24, 2021, the RMB exchange rate briefly rose to 6.48. After that, it was in a constantly fluctuating state until October 1, 2021. From October 1, 2021, to the end of the recording period, the RMB exchange rate began to fluctuate and drop to 6.36.



**Fig. 3** Chinese CER price

According to Fig.3, from the trend of the Chinese CER price in the figure, it can be seen that from July 16, 2021, to August 2021, the Chinese carbon price had a rapid decline after a short-term shock process, and the final price was 44 RMB per ton on September 6, 2021. After that, it experienced a relatively long plateau until December 8, 2021, and finally rose sharply to 58.5 RMB per ton at the end of the recording period.

### 3. Research methods

#### 3.1 DID

##### 3.1.1 Model Construction

Based on the basic statistical facts revealed by the above statistical analysis, we further evaluate the influences of China's entry into the carbon emissions trading market on European CER prices using the DID (Difference-in-Difference) model approach. The DID method is the most commonly used non-experimental method in policy evaluation, which can overcome the endogeneity problem to a large extent, so as to estimate the policy effect more accurately. China's entry into the carbon trading market can be regarded as a completely exogenous randomized experiment, which is consistent with the application conditions of the DID method. Specifically, we set the econometric model as:

$$P_t = \alpha + \beta_1 \text{treat}_t + \beta_2 \text{post}_t + \beta_3 \text{post}_t * \text{treat}_t + \beta_4 X_t + \epsilon_t \quad (1)$$

Where  $t$  represents the date,  $P$  represents the European CER price,  $\text{treat}_t$  represents the dummy variable of the treatment group. When  $\text{treat}_t = 1$ , it represents the treatment group.  $\text{post}_t$  represents the dummy variable of the time when China set up the national carbon emissions trading market, and when  $\text{post}_t = 1$ , it represents the time after China set up the national carbon emissions trading market, otherwise it is 0.  $\text{treat}_t$  indicates the level of the RMB exchange rate, which sets the data of the exchange rate below the average to 0, and the data of the exchange rate above the average to 1.  $X_t$  is the set of control variables, including the S&P 500 (Sp500) and the IPE Rotterdam coal futures closing price (Rot).  $\epsilon_t$  is the random perturbation term.  $\alpha$  is a constant term,  $\beta_1$ ,  $\beta_2$ , and  $\beta_3$  are variable coefficients, and  $\beta_4$  is a variable coefficient vector. If  $\beta_3$  is statistically significant, it means that China's entry into the carbon emissions trading market has a significant influence on European CER prices.

### 3.1.2 Variable description and data source

The explained variable is the price of CER in Europe. The data is from the European Energy Exchange. This variable can directly reflect the changes in European CER prices. Considering the completeness of the data, this paper used the daily data of the spot settlement price (EUR/ton) of European CER from February 5, 2021, to January 18, 2022.

The core explanatory variable is the shock of China's entry into the carbon emissions trading market(postt\*treatt), in which data with an exchange rate lower than the average is set as the control group, and data with an exchange rate higher than the average is set as the control group.

### 3.2 Prediction based on machine learning models

A machine learning method called Support Vector Machine (SVM) is developed from the "Optimal Hyperplane" solution method and based on the principle of Structure Risk Minimization (SRM). Due to its excellent learning performance and huge application potential, Support Vector Machine has become a popular method in the machine learning field, and has made great achievements in various fields such as personnel management, project evaluation, and risk prediction. In this paper, the machine learning method is used to make fitting predictions of European CER prices in four cases. The four cases are separate fitting predictions of European CER prices, and the fitting predictions of European CER prices after considering Chinese CER prices are carried out, forecasting the European CER price after considering the exchange rate of China against the US dollar, and forecasting the European CER price after considering the exchange rate of China against the US dollar and the European CER price. The specific research methods refer to the article Near-Infrared Spectrum of Coal Origin Identification Based on SVM Algorithm [8], which studies the influences of the opening of the Chinese carbon emissions trading market on CER prices in Europe.

Using Matlab 2018a software for Support Vector Machine modeling, it can be seen from the principle of SVM that the choice of kernel function directly determines whether the input space data can be converted into linearly separable data in the attribute space. For the data in this article, we plan to use comparative analysis to select a more appropriate kernel function. The training accuracy of the kernel function we selected and the Support Vector Machine model under each kernel function in the case of ten cross-validations is shown in the table. It can be seen that the training accuracy of the SVM model is high, and the best accuracy can be reached in the Medium Gaussian SVM model, so we choose the Medium Gaussian kernel function to test the prediction set.

In this study, we define the kernel function of a polynomial machine as follows:

$$K(x, x_i) = (x \cdot x_i + 1)^d \quad (2)$$

The polynomial kernel's kernel function and degree are  $K(x, x_i)$  and  $d$ . The framework training examples  $[x_i, y_i]$  are used in the training period. In another way, the method's input vector can be defined as  $x_i \in R^n$  &  $y_i \in (-1, 1), i = 1 \dots$

The optimal hyperplane of the binary decision class that divides the SVM definition and the main algorithm is:

$$Y = \text{sign}(\sum_{i=1} y_i \alpha_i (x \cdot x_i) + b) \quad (3)$$

## 4. Analysis of results

### 4.1 Variable description

**Table 1.** Variable Setting and Descriptive Statistics

| variable   | Variable meaning                                                        | average value | Max   | Minimum | Standard deviation |
|------------|-------------------------------------------------------------------------|---------------|-------|---------|--------------------|
| P          | European CER price                                                      | 56.84         | 88.88 | 36.90   | 12.61              |
| Treat      | Relative exchange rate                                                  | 0.51          | 1     | 0       | 0.50               |
| Post       | Before and after the opening of Chinese carbon emissions trading market | 0.38          | 1     | 0       | 0.49               |
| Treat*Post | the intersection of Post and Treat                                      | 0.21          | 1     | 0       | 0.41               |

### 4.2 DID benchmark regression results

**Table 2.** DID benchmark regression results

|            | (1)<br>Price         | (2)<br>Price         | (3)<br>Price         | (4)<br>Price         |
|------------|----------------------|----------------------|----------------------|----------------------|
| post       | 29.61***<br>(8.98)   | 29.39***<br>(8.86)   | 30.09***<br>(8.75)   | 29.86***<br>(8.64)   |
| Treat      | -4.427***<br>(-2.92) | -4.430***<br>(-2.92) | -4.436***<br>(-2.92) | -4.440***<br>(-2.92) |
| Post*Treat | -9.165***<br>(-4.52) | -9.157***<br>(-4.51) | -9.317***<br>(-4.54) | -9.305***<br>(-4.53) |
| Sp500      |                      | 0.000516<br>(0.70)   |                      | 0.000510<br>(0.69)   |
| Rot        |                      |                      | -0.00385<br>(-0.50)  | -0.00376<br>(-0.49)  |
| _cons      | 54.43***<br>(20.64)  | 52.36***<br>(13.24)  | 54.61***<br>(20.48)  | 52.56***<br>(13.19)  |
| N          | 227                  | 227                  | 227                  | 227                  |
| r2         | 0.674                | 0.675                | 0.675                | 0.676                |
| r2_a       | 0.670                | 0.669                | 0.669                | 0.668                |
| F          | 154.0                | 115.4                | 115.2                | 92.03                |

*t* statistics in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1 and 2 shows the regression results based on daily data on the spot settlement price (EUR/ton) of European CER from February 5, 2021, to January 18, 2022. The results show that the influences of China's entry into the carbon emissions trading market had a significant negative effect on the European CER price at the statistical level of 5%. This means the opening of the Chinese carbon emissions trading market has reduced the demand for the CER in Europe, and the devaluation of the RMB exchange rate will lead to a decrease in its conversion to euros, which will further lead

to a decrease in the demand for CER in Europe. Therefore, the depreciation of the RMB will also reduce the demand for CER in Europe.

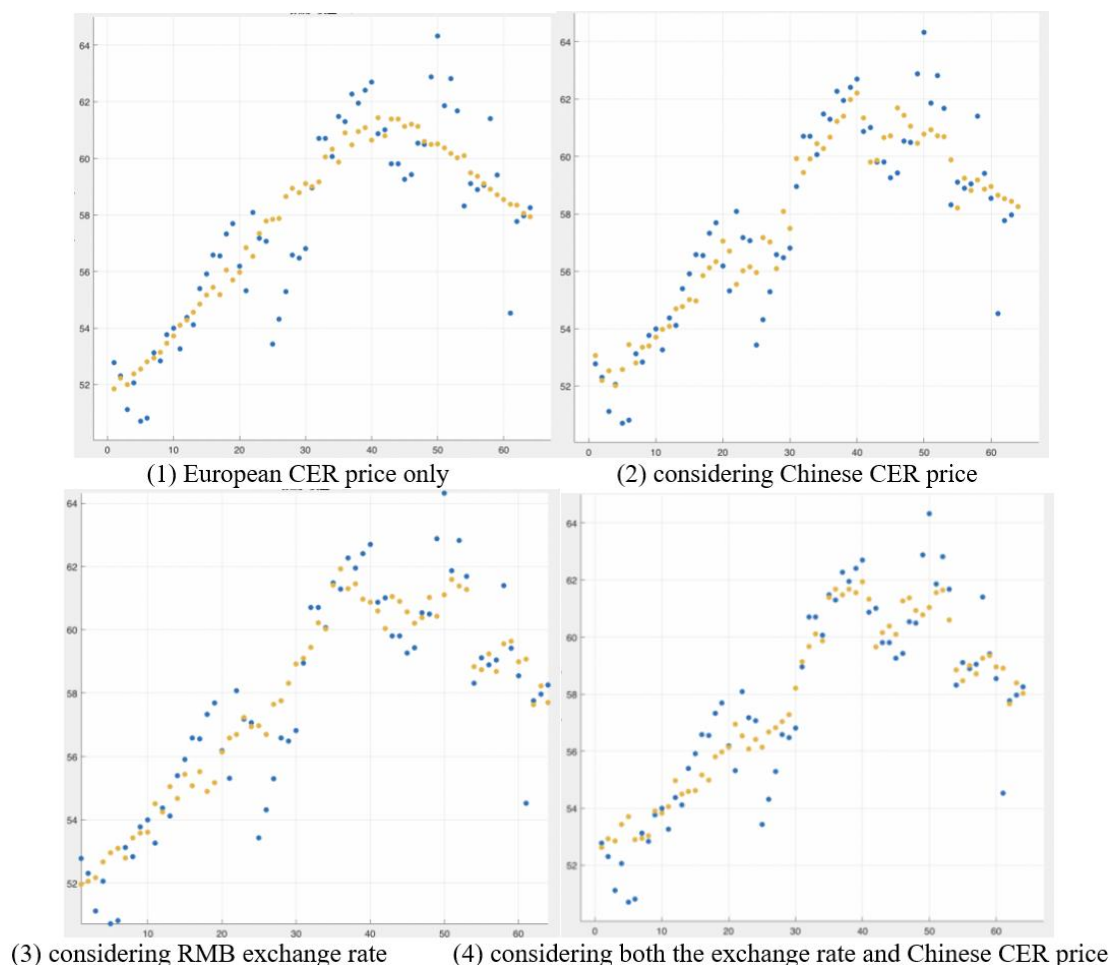
#### 4.3 The machine learning model predicts the results

According to the following fitting error analysis, the root means square errors of the following four situations range from 1.0989 to 2.4913. As for the Medium Gaussian SVM, the root mean square errors range from 1.316 to 1.746, the range is relatively low. When only the European CER price is fitted, the root means a square error of Medium Gaussian SVM is 1.746. After considering the two most significant considerations of Chinese CER price and exchange rate, the error dropped to 1.4342 and 1.4125 respectively, which indicates that the addition of the two considerations of Chinese CER price and exchange rate can optimize the fitting of European CER prices. This can confirm the argument that the Chinese CER price and exchange rate can affect the European CER price respectively. When adding the two considerations of Chinese CER price and exchange rate at the same time, the error dropped to 1.316, which further confirmed the above statement (Table 3).

Figure 4 below shows the fitting results. From the fitting effect, it can be seen that the accuracy of training using the SVM model is high, among which the Medium Gaussian SVM is the highest, so the Medium Gaussian SVM is used for figure fitting.

**Table 3.** forecasting results of a series of models.

| Model                  | (1)<br>European CER price<br>forecast |        |        | (2)<br>European CER price<br>forecast considering<br>Chinese CER price |        |        | (3)<br>European CER price<br>forecast considering the<br>exchange rate |        |        | (4)<br>European CER price<br>forecast considering<br>both the exchange rate<br>and Chinese CER price |        |        |
|------------------------|---------------------------------------|--------|--------|------------------------------------------------------------------------|--------|--------|------------------------------------------------------------------------|--------|--------|------------------------------------------------------------------------------------------------------|--------|--------|
|                        | RMSE                                  | MSE    | MAE    | RMSE                                                                   | MSE    | MAE    | RMSE                                                                   | MSE    | MAE    | RMSE                                                                                                 | MSE    | MAE    |
| Linear SVM             | 2.3849                                | 5.688  | 1.8811 | 2.4913                                                                 | 6.2064 | 2.0193 | 1.7205                                                                 | 2.9601 | 1.4572 | 1.6725                                                                                               | 2.7974 | 1.3409 |
| Quadratic SVM          | 1.7664                                | 3.1203 | 1.3129 | 1.623                                                                  | 2.6342 | 1.204  | 1.6056                                                                 | 2.5778 | 1.2923 | 1.6158                                                                                               | 2.6107 | 1.2312 |
| Cubic SVM              | 1.6135                                | 2.6035 | 1.2448 | 1.6817                                                                 | 2.8281 | 1.2637 | 1.7632                                                                 | 3.1087 | 1.4066 | 1.5171                                                                                               | 2.3016 | 1.1856 |
| Medium Gaussian SVM    | 1.746                                 | 3.0484 | 1.383  | 1.4342                                                                 | 2.057  | 1.1066 | 1.4125                                                                 | 2.0435 | 1.0713 | 1.316                                                                                                | 1.9678 | 1.0658 |
| Coarse Gaussian SVM    | 1.9988                                | 3.9953 | 1.6256 | 2.0981                                                                 | 4.4022 | 1.8022 | 1.9218                                                                 | 3.6932 | 1.5835 | 1.8391                                                                                               | 3.3821 | 1.5382 |
| Narrow Neural Net      | 2.3421                                | 5.4853 | 1.8559 | 1.5021                                                                 | 2.2562 | 1.1651 | 1.6379                                                                 | 2.6826 | 1.3558 | 1.6869                                                                                               | 2.8457 | 1.3064 |
| Bilayer Neural Net     | 1.5543                                | 2.4158 | 1.2142 | 1.3451                                                                 | 1.8093 | 1.0307 | 1.3573                                                                 | 1.8423 | 1.0794 | 1.4506                                                                                               | 2.1042 | 1.1378 |
| Three-layer Neural Net | 1.561                                 | 2.4369 | 1.1749 | 1.4806                                                                 | 2.1923 | 1.1058 | 2.1136                                                                 | 4.4673 | 1.5242 | 1.4636                                                                                               | 2.1423 | 1.0969 |



**Fig. 4** European CER price forecast

## 5. Conclusion

This paper takes the spot settlement price of European CER as the research samples and divides them into the treatment group and the control group based on the RMB exchange rate. By using the DID method to empirically estimate the spot settlement price panel data of European CER from February 5, 2021 to January 18, 2022, and supporting the analysis and fitting with a machine learning model, the research conclusions are as follows:

First of all, according to the existing articles, it is speculated that since changes in the external market will have an impact on the European CER price, China's entry into the carbon emissions trading market and the RMB exchange rate will affect the European CER price. However, there is no in-depth study on its specific impact process and mechanism. This paper makes up for the lack of research in this area and helps later studies to further expand new findings based on this research.

Secondly, the results of both the DID model and the machine learning model show that China's entry into the carbon emissions trading market has an important influence on the European CER price. The DID empirical results show that China's entry into the carbon emissions trading market hurts the European CER price. This paper analyzes the reason for this: after the opening of the Chinese carbon emissions trading market, companies with the need for carbon emissions have an additional way to obtain CER volume, which will reduce the demand for the European carbon emissions trading market. As demand falls, the European CER price falls.

Furthermore, from the DID empirical results, it can be seen that the devaluation of the RMB will also harm European CER prices. The reason is that the devaluation of the RMB will lead to a decrease in the amount of RMB converted into euros, so people will tend to buy carbon emission allowances in the Chinese market, which will further contribute to the decrease in the demand for CERs in the

European market. Therefore, the devaluation of the RMB will also reduce the need for CERs in Europe.

Finally, there are still shortcomings in this paper. Due to space limitations, no stability test is used to verify the stability of the model. In the future, the Propensity Score Matching method and robustness test can be considered to make the article more complete.

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