The Long-Term Trend Analysis and Scenario Simulation of the Carbon Price Based on the Energy-Economic Regulation

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Received 23 February 2020
Revised 1 June 2020
Accepted 1 June 2020

Abstract

Purpose – China's national carbon market will be officially launched in 2020, when it will become the world's largest carbon market. However, China's carbon market is faced with various major challenges. One of the most important challenges is its impact on the social and economic development of arid and semi-arid regions. By simulating the carbon price trends under different economic development and energy consumption levels, this study aims to help the government can plan ahead to formulate various countermeasures to promote the integration of arid and semi-arid regions into the national carbon market.

Design/methodology/approach – To achieve this goal, this paper builds a back propagation neural network model, takes the third phase of the European Union Emissions Trading System (EU ETS) as the research object and uses the mean impact value method to screen out the important driving variables of European Union Allowance (EUA) price, including economic development (Stoxx600, Stoxx50, FTSE, CAC40 and DAX), black energy (coal and Brent), clean energy (gas, PV Crystalox Solar and Nordex) and carbon price alternatives Certification Emission Reduction (CER). Finally, this paper sets up six scenarios by combining the above variables to simulate the impact of different economic development and energy consumption levels on carbon price trends.

Findings – Under the control of the unchanged CER price level, economic development, black energy and clean energy development will all have a certain impact on the EUA price trends. When economic development, black energy consumption and clean energy development are on the rise, the EUA price level will increase. When the three types of variables show a downward trend, except for the sluggish development of clean energy, which will cause the EUA price to rise sharply, the EUA price trend will also decline accordingly in the remaining scenarios.

Originality/value – On the one hand, this paper incorporates driving factors of carbon price into the construction of carbon price prediction system, which not only has higher prediction accuracy but also can simulate the long-term price trend. On the other hand, this paper uses scenario simulation to show the size,

The authors thank anonymous referees and editors for their constructive comments on the article. This work was supported by the West Program of the National Social Science Foundation of China (Grant No. 19XTJ003). However, authors are responsible for any error that remains.

This paper forms part of special section "Climate change impacts and adaptations in arid and semi-arid regions", guest edited by Zhihua Zhang, Qiang Zhang and Muhammad Jawed Iqbal.

International Journal of Climate Change Strategies and Management
Vol. 12 No. 5, 2020
pp. 653-668
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-02-2020-0020

direction and duration of the impact of economic development, black energy consumption and clean energy development on carbon prices in a more intuitive way.

Keywords Carbon price, EU ETS, Neural network model, Situational simulation

Paper type Research paper

1. Introduction

China's national carbon market is expected to become the world's largest carbon market and is critical for achieving China's domestic climate-change mitigation goals. But China's program is likely to face significant challenges, because of its complexity and large scale. While some of these challenges – such as emissions accounting, allowance allocation and market volatility – are common to emissions trading systems around the world, others are unique to China, because of its particular socioeconomic and political realities. One of the most important challenges is the impact of the construction of national carbon market on the social and economic development of arid and semi-arid regions in China. The arid and semi-arid regions of China account for more than 50% of the country's land area (Huynh *et al.*, 2019). Not only is there a shortage of water resources and a fragile ecological environment, but the economic development is backward and the industrial foundation is weak (Li *et al.*, 2019). In recent years, global warming has not only reduced the available water resources and biodiversity in the region, but also promoted its continuous expansion (Chapin and Díaz, 2020), which has exacerbated the uneven economic and social development of the eastern, central and western regions in China. The establishment of the national carbon market will inevitably have a huge impact on the social and economic development of the arid and semi-arid regions. Therefore, it is very necessary to predict the carbon price trend under different economic development and energy consumption levels, so as to be able to formulate various countermeasures in advance, turn crisis into opportunity and minimize the negative impact of carbon trading policies on arid and semi-arid regions.

2. Literature review

In recent years, research on the carbon market has been relatively rich. The research studies show that European Union Emissions Trading System (EU ETS), as the longest-running and relatively mature carbon market in the world, has shown obvious regularity in its market operation and price formation mechanism. However, there are relatively a few studies on the carbon price prediction, especially the prediction of the carbon price trend under different economic development and energy consumption levels. Therefore, predicting the trend of carbon price under different economic development and energy consumption scenarios also has important theoretical significance.

Price forecasting models are generally divided into three categories, including time series forecasting models based on the time series characteristics of the data itself, regression models based on the interaction between variables and combinatorial forecasting models that combine time series with multiple nonlinear regression (Sun and Duan, 2019). At present, the carbon price prediction methods also can be divided into data-driven and data-mining models. The data-driven model is a multiple nonlinear regression model based on the time series composed of carbon price, mainly using traditional econometric models, such as Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH), Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), Threshold AutoRegressive Conditional Heteroskedasticity (TGARCH), Vector Autoregressive (VAR) and Vector Error Correction (VEC). For example, Garda-Martos *et al.* (2013) used the multivariate GARCH model to predict the carbon price; and Byun and Cho (2013) used the

GARCH model to predict the carbon futures price volatility. Although data-driven models are usually well used for short-term analysis and prediction, the lack of economic implications of this method makes it impossible to explain the intrinsic driving force of carbon price changes. At the same time, with the increasing complexity of the socio-economic system and the continuous improvement of forecasting requirements, it becomes more and more difficult for data-driven models to meet actual needs. Data mining models can extract hidden and valuable information from a large number of fuzzy random data for non-stationary and non-linear time series prediction, and the prediction effect is significantly better than traditional econometric models (Zhao *et al.*, 2018). This type of model mainly includes gray theory, neural networks and support vector machines. For example, Tsai and Kuo (2014) used the Radial Basis Function Neural Network (RBFNN) model to predict carbon price; Sun *et al.* (2016) established a Variational Mode Decomposition Spiking Neural Network (VMD-SNN) model to predict EUA price; and Zhu and Wei (2013) constructed an Autoregressive Integrated Moving Average-Least Squares Support Veotor Maohine (ARIMA-LSSVM) model to predict carbon futures price. The prediction results of these models are all better than traditional time series prediction models.

The models for carbon price prediction in previous studies, whether from the perspective of data driving or data mining, only predict the carbon price based on the characteristics of time series data or the interaction between variables. Very few scholars have combined data-driven and data mining models to simulate and predict the carbon price trend. The artificial neural network model is a general function approximator that can map any nonlinear function without any a priori assumptions. It has a more powerful ability to capture the nonlinearity of the carbon price, and can integrate the development trend of the price itself and external factors to accurately simulate the long-term trend of carbon price under different economic development and energy consumption levels. As a supplement to traditional methods, the artificial neural network model has been widely used in the field of economics and finance. As the most widely used neural network model, back propagation (BP) artificial neural network model has good nonlinear mapping ability. It is not only good at processing incomplete, fuzzy and uncertain data, but also has obvious regularity, and it can also approximate multi-factor nonlinear complex systems well. It combines the advantages of data-driven and data mining models in price prediction. Therefore, on the basis of previous research, this paper intends to combine the carbon price itself with energy price, economic development and other external factors in market development to establish a carbon price prediction system. Scenario simulation of carbon price trends is conducted to analyze the impact of the establishment of the national carbon market on the social and economic development of arid and semi-arid regions in China.

3. Research design

3.1 Research object

China's seven major pilot carbon markets have been operating for more than seven years. As its development is still in its infancy, there are frequent non-transactions and a large number of transactions concentrated in the performance period during market operation. Therefore, the carbon price has not yet formed a good interactive relationship with the external market. As the longest and most mature carbon market in the world, the EU ETS has always been a model for other countries to learn. Although there are differences in the national conditions between the European Union (EU) and China, the design of the China's carbon market mechanism has been largely borrowed from the EU. By exploring the price trend of the EU ETS under different economic development and energy consumption levels, it also has a strong reference for the optimization of the China's carbon market mechanism.

The European Climate Exchange (ECX) is the carbon exchange with the largest trading volume of EU ETS. Its daily trading volume accounts for more than 80% of the total trading volume of EU ETS, and it can basically represent the price trend of EU ETS. Therefore, the research object of this article is the price of ECX futures trading products (EUA).

3.2 Variables selection

To build a carbon price prediction system based on the BP neural network model, we first need to screen out the main drivers of carbon price. Referring to the previous research studies, this paper pre-selects the certified emission reduction price to characterize the EUA price alternative; coal and crude oil price to characterize the development of black energy; the price of natural gas and the stock prices of two large European clean energy component production companies (PV Crystalox Solar and Nordex) to characterize the development of clean energy; and Stoxx600, Stoxx50, FTSE100, CAC40 and DAX index to characterize economic development, as driving variables for predicting the trend of carbon price under different economic development and energy consumption levels. Table 1 shows the description of the pre-selected variables for this article.

The above variables cover the period from January 2, 2013 to December 31, 2019, which includes all data for the third operational phase of the EU ETS.

To screen out the most important driving variables of carbon price, this paper uses mean impact value (MIV) algorithm to find the most important driving variables based on BP

Primary indicators	Secondary indicators	Description	Source
Carbon price	EUA	ECX carbon futures product price that account for more than 90% of the EU ETS transaction	Wind
Certified emission reduction price	CER	EUA's complementary product, which can be used to offset a certain percentage of carbon emissions	
Economic development	Stoxx600	Industrial development index across 18 EU countries is a barometer of EU industrial development	
	Stoxx50	The index can reflect the overall situation of stock prices of large listed companies in the Euro area, and its fluctuations directly affect the economic development of the EU	
	FTSE	A barometer of the British economy, it is also known as the three major European stock indexes together with the French CAC40 index and the German DAX index	
	CAC40	Barometer of French economic development	
	DAX	Barometer of German economic development	
Black energy	Coal	European CIF ARA coal price	EEX
	Brent	Brent crude oil futures price	ICE
Clean energy	Gas	EU natural gas price	
	PV Crystalox Solar	One of the UK's largest manufacturers of solar power materials, basically representing the status of clean energy development in Europe	Wind
	Nordex	One of Germany's largest manufacturers of wind power materials, basically representing the status of clean energy development in Europe	

Table 1.
Variable description

neural network. MIV can be used to reflect the change of the weight matrix in the neural network, and is considered to be one of the best indicators for evaluating the correlation of variables in the neural network. Therefore, this paper introduces the MIV method to evaluate the importance of each variable's impact on the carbon price. The symbol represents the relevant direction, and the absolute value represents the relative importance of the impact.

The specific calculation process is as follows:

- After the network training is terminated, each independent variable in the training sample P is added and subtracted by 10% on the basis of its original value to form two new training samples P1 and P2.
- P1 and P2 are used as simulation samples for network training to obtain two simulation results A1 and A2. The difference between A1 and A2 is the change value (IV) that affects the dependent variable after changing the independent variable.
- Finally, average the IV according to the number of observations to obtain the degree of influence of the independent variable on the dependent variable, which gives the MIV value.

Follow the above steps to calculate the MIV value of each variable in turn, and finally sort the influence degree of each variable according to the absolute value of MIV to get the relative importance of each variable to the dependent variable.

According to the MIV-BP neural network model, this paper obtains the degree of impact of each driving variable on the EUA price, in the order from large to small: Stoxx600 > Stoxx50 > CER > CAC40 > FTSE > DAX > Coal > Brent > Gas > Nordex > PV Crystalox Solar. Among them, five variables are strong influences and six variables are medium influences, all of which are important driving variables of EUA. Therefore, this paper selects all indicators in these four types of variables as the driving variables to simulate the trends of carbon price. Table 2 shows the calculation results of MIV.

3.3 Neural network model construction

3.3.1 Introduction of back propagation neural network model. BP neural network is a typical multi-layer feedforward neural network. Its main feature is the forward transmission of signals and the backward propagation of errors. In the forward pass, the input signal is processed from the input layer through the hidden layer to the output layer. The layers are

Primary indicators	Secondary indicators	Relativity	Strength
Substitute	CER	−0.2039	Strong
Economic development	Euro Stoxx600	0.2438	Strong
	Euro Stoxx50	−0.2290	Strong
	FTSE	0.1044	Strong
	CAC40	0.1232	Strong
	DAX	−0.0607	Medium
Black energy	Coal	0.0556	Medium
	Brent	−0.0484	Medium
Clean energy	Gas	0.0308	Medium
	PV Crystalox Solar	0.0270	Medium
	Nordex	−0.0327	Medium

Table 2. The degree of influence of each variable on the EUA price

connected in a fully connected manner. The neuron state of each layer only affects the state of the next layer, and there is no mutual connection between neurons of the same layer. If the output layer does not get the expected output, it goes to BP and adjusts the network weights and thresholds according to the error, so that the actual output of the BP neural network is constantly approaching the expected output (Khan and Khan, 2019).

The essence of the BP neural network is to attribute the error between the network output and the expected output to the error of the weight and threshold, and to distribute the error to the weight and threshold of each neuron through BP. The guiding idea of the BP network learning algorithm is that the adjustment of weights and thresholds should follow the direction of the fastest decline of the error function. Theoretically, the BP neural network has the ability to implement any complex nonlinear mapping, and is particularly suitable for solving problems with complex internal mechanisms, but it also has some limitations that are difficult to overcome. On the one hand, too many hidden layer neurons will cause over-learning, and too few neurons will lead to under-learning. On the other hand, the BP algorithm can theoretically achieve any nonlinear mapping, but in practical applications, it may often fall into the local minimum. At this time, it is necessary to obtain the global optimal value by changing the initial value and running multiple times.

3.3.2 Construction of back propagation neural network model. BP neural network modeling includes three steps: BP neural network framework construction, BP neural network training and BP neural network prediction.

3.3.2.1 Model framework construction. *Number of network layers*: Hidden layers can be divided into single and multiple hidden layers according to the number of layers. The multi-hidden layer is composed of multiple single-hidden layers. Compared with the single-hidden layer, the multi-hidden layer has strong generalization ability, high prediction accuracy but long training time. For complex mapping relationships, multiple hidden layers can be selected to improve the prediction accuracy of the network. To ensure the accuracy of price prediction, this article sets the hidden layer to two layers, which makes the prediction accuracy of the model further improved.

Number of neurons: The BP neural network model has a total of 11 input variables in this paper, including CER, Stoxx600, Stoxx50, FTSE, DAX, CAC40, Brent, Coal, Gas, Crystalox Solar and Nordex. Therefore, the number of input layer neurons is 11. Because the output variable only has the EUA price, the number of output layer neurons is 1.

Number of hidden layer nodes: The number of hidden layer nodes has a great influence on the prediction accuracy. If the number of nodes is too small, the network will not be able to learn well. The model needs to increase the number of trainings, and the accuracy of training will also be affected; if there are too many nodes, the training time will increase, and the network is also likely to overfit. The best hidden layer node number selection can refer to the equations (1), (2) and (3):

$$\sum_{i=0}^{n} C_M^i > k \tag{1}$$

$$M = \sqrt{n+m} + a \tag{2}$$

$$\mathrm{M} = \sqrt{\mathrm{n}+m} + a \tag{3}$$

In the equations (1), (2) and (3), M is the number of neurons in the hidden layer, n is the number of neurons in the input layer, m is the number of neurons in the output layer, a is a constant between 0 and 10 and k is the number of samples. If $i \geqq M$, then $C_M^i = 0$. In practical problems, the choice of the number of nodes in the hidden layer is to first refer to equations (1), (2) and (3) to determine the approximate range of the number of nodes, and then use the trial and error method to determine the optimal number of nodes.

According to the empirical formula, the range of the number of hidden layer neurons determined is 4 to 14, and the Mean Squared Error (MSE) value corresponding to the number of different hidden layer neurons is obtained through the test model to determine the optimal number of hidden layer neurons. When the MSE is the smallest, it indicates that the model is optimal. The optimal number of hidden layer neurons is 12 in this paper. To ensure the accuracy of the price prediction, this paper sets the hidden layer to two layers, which will further reduce the MSE value of the model.

$$\mathrm{MSE} = \frac{1}{\mathrm{m}} \sum_{m=1}^{\mathrm{m}} \left(y_m - \hat{y_m} \right)^2 \tag{4}$$

In equation (4), m is the total number of test samples, y_m is the real value and $\hat{y_m}$ is the predicted value. The smaller the value, the better the model prediction effect.

Determination of neuron transfer function: The choice of hidden layer and output layer functions has a great influence on the accuracy of the BP neural network. It is usually necessary to test different neuron transfer functions multiple times to determine the optimal transfer function. Generally, the hidden layer uses the sigmoid function and the output layer uses the linear function. If the output layer also uses the sigmoid function, the output value will be limited to (0, 1) or (−1, 1). After multiple tests and comparisons, the transfer function of the hidden layer neurons is the tangent S-type transfer function *logsig* [equation (5)]. The transfer function of output layer neurons is linear transfer function *purelin* [equation (6)].

$$\log sig(n) = \frac{1}{1 + e^{-n}} \tag{5}$$

$$y = x \tag{6}$$

Selection of training methods: The choice of training algorithm is related to the problem itself and the number of training samples. Generally, for a function approximating network with hundreds of weights, the Levenberg–Marquardt (LM) algorithm has the fastest convergence speed and the MSE is relatively small. Therefore, the model selects the LM algorithm as the training function, which can effectively overcome the deficiencies of slow convergence and local minima that are commonly found in gradient descent, Newton and conjugate gradient methods. The training function of the BP algorithm is *Trainlm*, the learning function is the BP learning rule *Learngdm* with momentum and the performance analysis function selects the mean squared error performance analysis function MSE. After the training function is designed, it is necessary to further optimize the model training parameters. The final training function parameters are:

$$net.trainParam.epochs = 10^4, Maximum\ \ number\ \ of\ \ iterations \tag{7}$$

$$net.trainParam.lr = 10^{-2}, Learning\ rate\ setting \tag{8}$$

$$net.trainParam.goal = 10^{-7}, Target\ error\ of\ neural\ network\ training \tag{9}$$

$$net.trainParam.min\_grad = 10^{-7}, Minimum\ performance\ gradient \tag{10}$$

$$net.trainParam.max\ fail = 10^{2}, Maximum\ confirmation\ failure\ number \tag{11}$$

3.3.2.2 Back propagation neural network training. *Normalized data*: The inconsistency of the prior information of the sample data will make the training error of the neural network larger. Therefore, it is necessary to preprocess the sample data to eliminate the magnitude difference of variables. In the BP neural network, the *mapstd* and *mapminmax* function is often used for normalization to avoid large network prediction errors because of large differences in the magnitude of input and output data. The sample data shows that the normalized data of the *mapstd* function is more stable than the *mapminmax* function. Therefore, this paper uses the *mapstd* function for data preprocessing. The pretreatment formula is:

$$\mathrm{y} = (x - x_{mean})(y_{std}/x_{std}) + y_{mean} \tag{12}$$

In the equation (12), x is the original sample data and y is the new data after conversion. Among them, $y_{std} = 1$ and $y_{mean} = 0$.

The accuracy of BP neural network prediction has a great relationship with the amount of training data. Especially for a multi-input and multi-output network, if there is not enough network training data, the network prediction value may have a large error. In this paper, 80% of the data is randomly selected as the training sample set, and the BP neural optimal network is constructed through multiple training; the remaining 20% is used as the test sample to test the model generalization ability. The total sample of EUA price and other variables is 1,792 groups, of which 1,434 groups (80%) are randomly selected training sample and 358 groups (20%) are test sample.

According to the established neural network model, 80% of the randomly selected sample is trained, and the minimum MSE value is used as the basis for selecting the optimal model. After repeated experiments, the key parameters of the optimal BP neural network selected in this paper are shown in equations (13), (14) and (15).

$$net.trainParam.goal = 10^{-5} \tag{13}$$

$$net.trainParam.max\ fail = 100 \tag{14}$$

$$net.trainParam.epochs = 96 \tag{15}$$

Although the optimal setting is not reached, the maximum number of failures has reached 100, and the neural network has achieved convergence.

3.3.3 Back propagation neural network test. Based on the optimal parameters selected above, another 20% of the samples are tested to obtain the percentage of error predicted by the model. The average relative error value is only 0.000922, MSE = 0.2805 and the relative residual is basically between −0.2% and 0.15%. This shows that the BP neural network has high prediction accuracy and small error, and can be used for scenario simulation of EUA price trends.

4. Carbon price trend scenario simulation

4.1 Scenario building

Based on the established optimal BP neural network, this paper simulates the scenarios that the carbon market may encounter by combining economic development and energy consumption variables, and then predicts the EUA price trend. First, the model controls the steady consumption of clean energy and black energy, and discusses the EUA price trend under the scenario of high-speed and low-speed economic development. This provides a reference for judging the possible impact of arid and semi-arid regions when they are included in the carbon market together with regions with high economic development. Second, the model controls the economy and the development of clean energy is stable, and discusses the EUA price trend under the black energy consumption shock and recession scenario, which provides a reference for judging whether arid and semi-arid regions should be included in the carbon market with low-energy regions. Third, the model controls economic development and black energy consumption unchanged, and explores the EUA price trend under the scenario of vigorous development and recession of clean energy, which provides a reference for judging of the impact of the vigorous and sluggish development of clean energy on carbon price.

Relying on the above assumptions, this paper realizes the purpose of scenario simulation by controlling the two types of variables to remain unchanged and changing the fluctuations of the third type of variables. In the scenario simulation, the maximum fluctuation value of each carbon price driver is determined based on the ratio of the maximum and minimum values compared to the average values of the above variables from January 2, 2013 to December 31, 2019. Table 3 shows the historical changes and historical averages of various variables.

Take Stoxx600's growth of 44.95% as an example to explain the numerical construction method of input variables in the model during scenario simulation:

Variable	Maximum increase(%)	Maximum decrease(%)	Historical mean (Stable value)
Economic development			
Stoxx600	44.95	−24.55	356.97
Stoxx50	40.42	−28.33	3019.09
FTSE	34.41	−19.33	6891.04
CAC40	36.24	−22.91	4780.27
DAX	35.83	−22.75	10829.65
Black energy			
Brent	164.14	−70.81	71.07
Coal	143.91	−53.94	72.89
Clean energy			
Gas	123.90	−67.41	49.23
PV Crystalox Solar	249.08	−71.47	21.13
Nordex	759.74	−75.23	14.60
Substitute			
CER	1650.00	−294.12	0.28

Table 3. Historical mean and fluctuation of each variable

- Set the duration of scenario prediction to n months.
- To approximate the realistic simulation effect, this article carries out conditionally random values for each variable. First, set the initial value to the mean x of the previous year's data. Then, set the upper limit of numerical growth to x and the lower limit to y. If it is negative growth, reverse the upper and lower numerical limits. When randomly generating $n-1$ values, two conditions must be satisfied at the same time. On the one hand, the mean value of x and these $n-1$ random values is x (1 + 44.95%). On the other hand, the growth trend of x and these n-1 random values is consistent with the expected trend.
- Taking the random average value of $n-1$ months as the value of the last day of each month, the initial value of the next month is the end value of the previous month plus the value of the random disturbance.

To match the values of the six scenarios, this paper directly takes the maximum fluctuation value of each variable, which are the average changes in each scenario. For variables that need to be changed smoothly, the historical mean value after fluctuation is used. Table 4 shows the specific values of each scenario.

4.2 Scenario simulation results and analysis

In this paper, the data of each scenario is input into the BP neural network that has been established, and the changes in economic development and energy consumption variables are regulated and controlled separately to realize the scenario simulation of the EUA price trend. Figure 1 shows the output results in each scenario.

Figure 1 shows the simulation results of the EUA price trend under six typical scenarios. Under the control of the unchanged CER price level, economic development, black energy and clean energy development will all have a certain impact on the EUA price trends. Among them, when economic development, black energy consumption and clean energy development are on the rise, the EUA price level will increase. When the three types of variables show a downward trend, except for the sluggish development of clean energy, which will cause the EUA price to rise sharply, the EUA price trend will also decline accordingly in the remaining scenarios. In general, the impact of changes in economic development and energy consumption on the EUA price trends differs in size, direction, duration of action and mode of impact.

When the economy grows, the EUA price trend will fluctuate sharply, and it will quickly drop from €42.79/ton to €3.82/ton, and then rise to €35.28/ton in three years. In the past year, the EUA price trend showed a "V" shape and continued to grow. The average carbon price during the simulation period is €19.42/ton, much higher than the real average price of €10/ton. This shows that economic growth has a significant promotion effect on the EUA price level, but this promotion effect mainly affects the price level rather than trend. The price trend may still be affected by other factors and exhibit a substantial downward trend. When the economic growth shows a downward trend, the EUA price will plummet to €2.18/ton in one month, and then will fluctuate greatly in the price range of €2–15/ton for a long time, and will converge to the €6/ton price level at the end of the period. During the simulation period, the average market price is €8.38/ton, slightly lower than the real average market price. This shows that because of the impact of the decline in economic development, EUA price will plummet in the short term. However, under the existing mechanism of the carbon market, it is difficult for the EUA to maintain low-price operation for a long time and thus shows a trend of large shocks. After the market operates smoothly, the price will converge to a lower level.

Scenario type	Economic development					Black energy			Clean energy		Substitute
	Stoxx600	Stoxx50	FTSE	CAC40	DAX	Brent	Coal	Gas	PV Crystalox Solar	Nordex	CER
Rapid economic growth	44.95%	40.42%	34.41%	36.24%	35.83%	71.07	72.89	49.23	21.1	14.60	0.28
Rapid economic recession	−24.55%	−28.33%	−19.33%	−22.91%	−22.75%	71.07	72.89	49.23	21.13	14.60	0.28
Black energy development	356.97	3019.09	6891.04	4780.27	10829.65	164.14%	143.91%	49.23	21.13	14.60	0.28
Black energy decline	356.97	3019.09	6891.04	4780.27	10829.65	−70.81%	−53.94%	49.23	21.13	14.60	0.28
Clean energy development	356.97	3019.09	6891.04	4780.27	10829.65	71.07	72.89	123.90%	249.08%	759.74%	0.28
Clean energy decline	356.97	3019.09	6891.04	4780.27	10829.65	71.07	72.89	−67.41%	−71.47%	−75.23%	0.28

Table 4. Typical scenario setting outside the carbon market

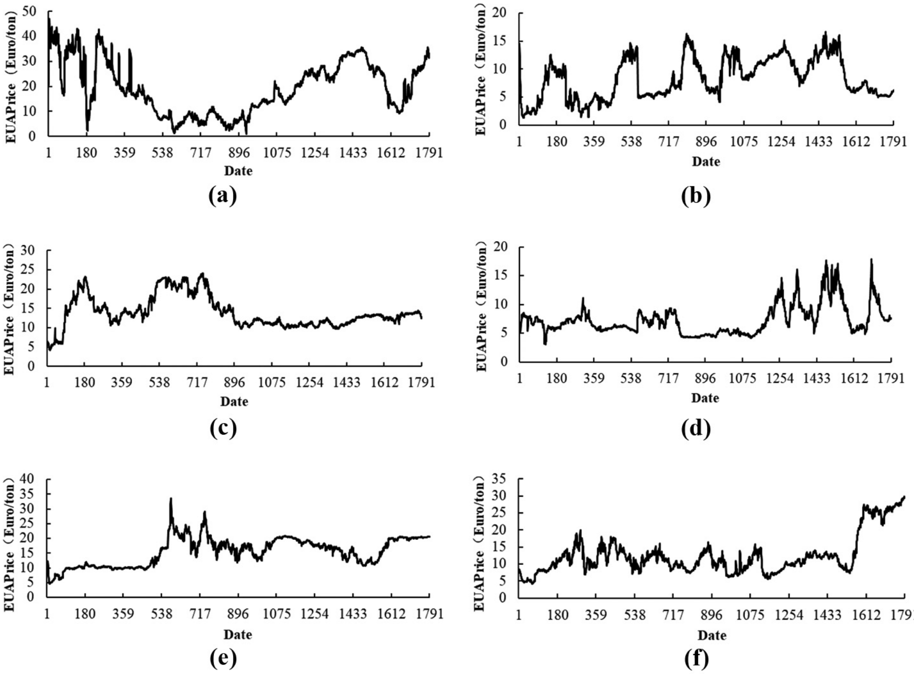

Figure 1.
Carbon futures price trend under six typical scenarios

Notes: (a) Economic growth scenario; (b) economic recession scenario; (c) black energy consumption rising scenario; (d) black energy consumption decline scenario; (e) rapid development of clean energy; (f) weak development of clean energy

When the consumption of black energy rises, the EUA price will rise to €22.13/ton within half a year. After a period of price fluctuations, the EUA price will stabilize at €11/ton in the fourth year and show a slow growth trend. The average market price during the simulation period is €13.98/ton, slightly higher than the real average market price. This shows that the huge impact of rising black energy consumption on the EUA price trend is rapid but relatively short-lived, and it has no obvious effect on the market price level after convergence. When black energy consumption declines, the EUA price will run smoothly at a price level of €4–5/ton for a long time, and it will show a large fluctuation trend at the end of the period. The average market price during the simulation period is €7.32/ton, which is lower than the real average market price. This shows that the negative impact of black energy consumption on the EUA price trend is slow and lasts longer.

With the rapid development of clean energy, the EUA price fall briefly to €6.37/ton at the beginning of the period, and then fluctuate around €10/ton for a long time. However, after the third year, the EUA price begins to fluctuate, and converge to the €20/ton at the end of the period. The average market price is €15.49/ton, which is higher than the real average market price. This shows that the rapid development of clean energy will promote the continuous increase of carbon price until it can gradually reflect the cost of emission reduction by enhancing the development expectations of market participants and optimizing energy structure. When the development of clean energy is weak, the EUA price quickly rise from €4.96/ton to €19.33/ton after a brief decline, and then fluctuate around €14/

ton for a long time. At the end of the period, the EUA price rise from €9.47/ton to €25.95/ton, and there is a tendency to continue to rise. During the simulation period, the average market price is €12.39/ton, slightly higher than the real average market price. This shows that the weak development of clean energy has a certain positive effect on EUA price, and this positive effect has an upward trend with time.

4.3 Discussion

Comparing the prediction results under the scenario of rapid economic growth [Figure 1(a)] and recession [Figure 1(b)], it can be seen that when the economically backward arid and semi-arid regions and the fast-growing eastern and central regions are simultaneously included in the carbon market, on the one hand, because of the dependence of the energy structure and the high cost of overall emission reduction, if the emission control companies in arid and semi-arid regions do not reduce emissions, they will have to bear the high carbon price dominated by the eastern and central regions, which increase the operating costs of emission control companies and hinder local economic development. On the other hand, if emission control companies in arid and semi-arid regions reduce emissions to avoid high carbon price costs, the unit emission reduction cost in arid and semi-arid regions is lower than that in the central and eastern regions, which may cause the region to become a quota export for the entire market. By then, the carbon market will be reduced to a disguised subsidy and thereby weaken the market's overall emission reduction capacity. Therefore, at the initial stage of the national's carbon market, the proportion of free quota allocation for pillar industries in arid and semi-arid regions should be appropriately increased, and the free quota should be gradually tightened when the market is mature.

The level of energy consumption determines the quota demand and emission reduction potential of emission control companies. Comparing the prediction results under the scenarios of high energy consumption [Figure 1(c)] and low energy consumption [Figure 1(d)], it can be seen that the emission demand and emission reduction potential of low energy consumption enterprises are not high, and they are more inclined to purchase quotas to complete compliance, so they will have to withstand the high carbon price dominated by high energy consumption enterprises. Therefore, in the initial stage of carbon market establishment, the market access threshold can be appropriately increased to include only high-energy-consuming enterprises in arid and semi-arid regions. When the market is mature, it will be gradually included in low-energy enterprises.

The development of clean energy will affect the carbon price by affecting the energy structure of enterprises and market expectations. Comparing the prediction results under the scenarios of rapid development [Figure 1(e)] and recession [Figure 1(f)] of clean energy, it can be seen that the rapid development of clean energy can effectively promote the steady rise of carbon price through energy cost conversion and enhancement of market expectations. Under the recession scenario, because of the inherent energy structure and compliance constraints, the increase in corporate emissions demand will also promote carbon price. Therefore, during the construction of the national carbon market, the development of clean energy such as wind power and solar power in arid and semi-arid regions can to some extent enhance the development expectations of enterprises to stabilize carbon price. At the same time, it is also necessary to prevent the negative impact of the clean energy development recession on market expectations.

5. Conclusions and policy suggestions

5.1 Conclusions

According to results, this study found:

- Economic growth has a significant promotion effect on the EUA price level, but this promotion effect mainly affects the price level. The economic recession will cause the EUA price to plummet in the short term, but the EUA price trend under the constraints of compliance will show long-term shock.
- The huge impact of rising black energy consumption on the EUA price trend is rapid but relatively short-lived, and it has no obvious effect on the carbon price level after convergence; however, the negative impact of black energy consumption decline is slower and lasts longer.
- The rapid development of clean energy will promote the rise of carbon price by enhancing the development expectations of market participants and adjusting the energy consumption structure.

The weak development of clean energy also has a positive effect on EUA price, and this positive effect has a rising trend.

5.2 Policy suggestions

According to the research conclusion of this paper, in the face of the upcoming national carbon market, this paper proposes the following policy recommendations for the mechanism design of arid and semi-arid regions:

- Vigorously develop clean energy and relax restrictions on the proportion and types of certified emission reductions. Although arid and semi-arid regions have lagging economic development and numerous high-energy-consuming enterprises, they have a large number of wind power, solar power and certified emission reduction resources. To minimize the negative impact of the national carbon market, on the one hand, arid and semi-arid regions can vigorously develop various types of clean energy and sell them to the eastern and central regions for a fee to promote the upgrading of the energy structure. On the other hand, the sources of certified emission reductions in the eastern and central regions should give priority to arid and semi-arid regions to achieve ecological compensation for the region, and the certified emission reduction ratios and types of arid and semi-arid regions can be appropriately relaxed. For example, the proportion of certified emission reduction can be 10–20% higher than the national average level, and the scope of certified emission reduction types can be appropriately extended to hydropower, biogas and other projects.
- Appropriately raise the market access threshold for emission control companies in arid and semi-arid regions. In the early stage of China's national carbon market, only more than 1,700 power generation companies with an annual carbon emission of more than 26,000 tons are included, but this is still relatively high compared to the market access threshold for China's Hubei pilot carbon market with annual emissions of 150,000 tons. In particular, the social and economic development of arid and semi-arid regions is still far behind that of Hubei province, so this threshold is not conducive to the development of emission control companies in arid and semi-arid regions. Therefore, the market access threshold for emission control companies in arid and semi-arid regions can be appropriately increased compared to the eastern and central regions. For

example, referring to the Hubei pilot experience, the market access threshold is also set to an annual emission of 150,000 tons or higher.

- Properly increase the proportion of free quota allocation for pillar industries in the economy, and gradually tighten the proportion of free quota when the market is mature. Although the national carbon market only included power generation companies in the early stage, it is caused by the inability to accurately grasp the accurate verification data of emission control companies in other industries. When the market is mature, seven major industries including petrochemicals, nonferrous metals, chemicals, papermaking, building materials, steel and aviation will also be gradually included in the national carbon market. However, most of the above industries are pillar industries for economic development in arid and semi-arid regions. To avoid excessive impacts on the economic development of arid and semi-arid regions by the carbon market, the government can appropriately increase the proportion of free quota allocation for pillar industries in the economy and gradually tighten the proportion of free quotas when the market is mature.

Finally, during the construction of the national carbon market, while treating the mechanism design of arid and semi-arid regions differently, relevant measures should be set up to prevent carbon leakage.

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Further reading

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