RESEARCH ARTICLE

Key factors affecting carbon prices from a time-varying perspective

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Abstract
For humankind to sustain a livable atmosphere on the planet, many countries have committed to achieving carbon neutralization. Countries mainly reduce carbon emissions by regulations through a carbon tax or by establishing a carbon market using economic stimuli. In this paper, we use the least absolute shrinkage and selection operator (LASSO) method to select the key determinants of a carbon market and then use the Markov switching vector autoregression (MSVAR) model to study the market’s driving factors and analyze its time-varying characteristics. The results show that there are perceptible time-varying characteristics and notable differences among markets. During COVID-19, energy factors had a long-term shock on the carbon market, economic factors had a short-term shock on the carbon market, and the economic recession has led to fluctuations in the carbon market. In addition, through MSVAR, the results show that the energy market has a negative effect on the carbon market, and the stock market has a positive effect on the carbon market. In periods of low volatility, compared with the natural gas market and coal market, the oil market has a stronger shock on the carbon market. In periods of high volatility, the coal market has a stronger shock on the carbon market. In terms of emission reduction, countries around the world would be wise to change their energy consumption structure, reduce coal use, and shift to a cleaner energy consumption structure.

Keywords EU ETS · Carbon price · Markov switching · VAR · LASSO

Introduction
Since the industrial revolution in the nineteenth century, rapid economic development has led to the intensification of energy consumption. Fossil energy, proportionally the highest source of energy consumption, produces a large amount of carbon dioxide in the process of burning. As a kind of greenhouse gas, the uncontrolled emission of carbon dioxide leads to a deleterious warming greenhouse effect for the entire planet. At present, the global temperature is generally rising, which has begun to pose a series of threats to the continued survival of human beings, such as the rise in sea levels caused by glacier melting, a food security crisis caused by extremely cold and hot climates, and a reduction in species diversity caused by damage to numerous ecosystems. An increasing number of countries are making global climate change a national priority. There is a growing consensus in the international community of the need to reduce carbon dioxide emissions and protect the global climate.

Looking at the total carbon emissions of the world and the 27 EU countries, as shown in Fig. 1, it is apparent that the total carbon emissions of the world have increased significantly in the last three decades, while the total carbon emissions of the EU are relatively stable. The main reason for the increase in world carbon emissions is the booming economic development and increased energy demand of some developing countries, such as China; and many countries meet their energy growth needs through fossil energy combustion. The EU has established the EU carbon emission trading system to reduce carbon emissions through market mechanisms, and total carbon emissions are projected to remain at a stable level and even decrease after 2005. To prevent the continuous deterioration from climate change and ensure steady and
rapid economic growth, countries have taken active actions to address climate change effects. In December 1997, the Kyoto protocol was adopted in Kyoto, Japan, to guide developed countries in implementing the task of greenhouse gas emission reduction. The convention allows developed countries to trade carbon emission allowances. In 2016, the Paris Agreement included developing countries in the emission reduction targets and they joined in the implementation of emission reduction targets. The USA, Japan, Brazil, and the European Union have successively promised to achieve the aim of carbon neutralization by 2050. China is also striving to achieve a carbon peak in 2030 and carbon neutralization in 2060.

At present, countries use a carbon pricing mechanism to control carbon dioxide emissions by means of economic stimulus. The main economic methods are to set up a carbon tax or establish a carbon emission trading market. The trade participants of the carbon emission trading market are all enterprises included in the scope of the emission reductions, and the trading products are carbon emission allowances. The supply of carbon allowances is instituted by the government, allocated to enterprises according to certain rules, and decreases year by year. If the enterprise’s carbon emission exceeds the agreed-upon carbon emission allowance within the agreed time, it purchases carbon emission allowances on the market; otherwise, it faces fines from the regulatory authority. In contrast, if an enterprise develops energy-saving and emission reduction technologies to improve energy efficiency, resulting in less carbon emissions than the given carbon emission allowance, the excess carbon emission allowance can be sold, and the enterprise can make a profit. The EU first launched its first carbon dioxide emissions trading system in 2005, the EU emissions trading scheme (EU ETS), which is also the largest carbon emissions trading market at present. The EU ETS plays an important guiding role in the establishment of carbon emission trading markets all over the world. Exploring the impact mechanisms of carbon prices will help countries make reasonable carbon pricing decisions to give full play to the role of carbon pricing and better achieve the emission reduction targets.

At present, many studies have analyzed the factors influencing the carbon market (Alkathery and Chaudhuri 2021; Boersen and Scholtens 2014; Carnero et al. 2018). Chevallier (2009), Mansanet-Bataller et al. (2011), Tan and Wang (2017), and Ji et al. (2018) believe that the influencing factors of the carbon market are mainly divided into two categories, energy factors and macroeconomic factors. Mansanet-Bataller (2006) pointed out that coal prices and Brent prices from energy factors will affect carbon prices. Creti et al. (2012) show that there is a long-term cointegration relationship among oil prices, natural gas prices, and coal prices for energy factors, as well as for both the stock price index and carbon price. Aatola et al. (2013) applied VAR models to find that electricity prices in the commodity market are a key determinant of carbon prices. Zhang and Zhang (2018) applied the ARDL model to consider the impact of the exchange rate market on China’s carbon emissions. Jiménez-Rodríguez (2019) used the time-varying parameter model to analyze the Granger causality for both the European stock market and carbon market at different stages. Zhao et al. (2021) used the mixed decomposition and integrated forecasting model to find that energy factors and economic factors can contribute to the improvement of carbon price forecasting accuracy. Wang and Zhao (2021) studied the impact and transmission path of the stock market and energy.
market on the carbon market by using a structural equation model. In research on the volatility spillover of the carbon market, Chevallier (2009) used a variety of GARCH models to prove that the volatility of carbon prices is affected by the stock market and bond market. Zhang and Sun (2016) used DCC-TGARCH and BEKK-GARCH models to explore the spillover effect between the energy market and carbon market and found that there is a strong correlation between the coal market and the carbon market (Dong et al. 2021; Yu et al. 2020; Nie et al. 2021). Wang and Guo (2018) and Adekoya et al. (2021) used the spillover index structured by Diebold and Yilmaz (DY) to analyze the time-varying spillover effects. Gong et al. (2021) analyzed the time-varying characteristics between markets by using the TVP-VAR-SV model, and the results show that the transmission of both the energy market and the carbon market is different in different periods.

From the above literature, it can be confirmed that there is either a strong or weak interaction among the carbon market, energy market, and macroeconomic factors (Chang et al. 2020; Chevallier 2012). In addition, many studies show that there is a structural break in carbon price fluctuations (Alberola et al. 2008; Tan and Wang 2017; Tan et al. 2020; Wang et al. 2021). However, in the current carbon market research, most models either do not consider non-linear modeling, cannot consider the time-varying characteristics of the interaction between markets, or need to estimate multiple parameters in modeling. The MSVAR model can analyze the structural break of carbon price fluctuations from the perspective of time variations and consider the effects of the energy market and macroeconomic factors under different regimes (Dong et al. 2021a). At present, MSVAR is extensively used in various fields, especially in the energy economy. Chevallier (2011) uses the MSVAR model to consider the impact of macroeconomic activities on carbon prices. Based on the MSVAR model, Roubaud and Arouri (2018) found that the exchange rate and stock market will have a significant negative impact on the oil market in a high volatility period. Chen et al. (2019) studied the impact of financial factors on copper price fluctuations by using the MSVAR model with three regimes. The results show that financial factors have an increasing impact on non-ferrous metal prices. Shahrestani and Rafei (2020) investigated the impact of oil market shocks on the stock market based on the MSVAR model and found that oil shocks had the opposite effect on the stock market under different regimes.

In addition, it can be found that there are many influencing variables in the carbon market, which would result in too many estimated parameters, so it is necessary to select the key determinants affecting the carbon market. Feature selection methods are widely used in many fields, among which the least absolute shrinkage and selection operator (LASSO) is the most common method and has a good performance. Li and Chen (2014) found that in macroeconomic time series prediction, the performance of all LASSO prediction models is better than that of the dynamic factor model. Nazemi and Fabozzi (2018) predicted the yield of US corporate bonds and found that the macroeconomic variables selected by LASSO significantly improved the prediction performance of the yield. Miao et al. (2017) and Zhang et al. (2019) used the LASSO model to select the characteristics of multiple macroeconomic variables. The results show that the prediction model using the selected factors in oil price prediction is better than other benchmark models.

Using data on the carbon market, energy market, and financial market from 2016 to 2021, this study investigates the influencing factors and mechanisms of carbon prices. This paper’s main research contributions are as follows: (1) Based on the LASSO model, a time window is introduced to investigate the influencing factors of carbon prices at different times to make the selection of influencing factors of carbon prices more reasonable and to determine the key determinants affecting carbon prices. (2) Considering a possible structural fracture, the MSVAR model is constructed to study the impact mechanisms of the energy market and stock market on the carbon market under different fluctuation conditions. (3) Impulse response analysis is used to further explore the short-term dynamic impact between markets under different fluctuation states and their transmission size and direction. This paper enriches the literature that considers time-varying characteristics and market mechanisms and provides policy suggestions for governments and enterprises to promote emission reductions.

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**Methods**

**Mechanism analysis**

At present, research on the influencing factors of carbon prices is reflected in energy price factors, macroeconomic factors, and policy and weather factors. The development of enterprises is inseparable from energy consumption, and the energy price affects the energy demand and energy structure, which will inevitably affect the carbon emissions of enterprises, thus affecting the carbon price (Dong et al. 2021b). Macroeconomic factors reflect the level of economic development. At different development stages, enterprises’ demand for energy will vary, resulting in changes in carbon prices. In this study, we intend to analyze the role of the energy market and stock market on the carbon market, and its mechanism is shown in Fig. 2.
The combustion process of fossil energy produces a large amount of carbon dioxide, which has an impact on the demand for carbon emission allowances of enterprises and eventually leads to a change in carbon prices (Umar et al. 2020). The rise of fossil energy prices is first reflected in an increase in enterprise production costs and a reduction of enterprise profits, so enterprises consider reducing production. The reduction of carbon dioxide emissions means that the demand for carbon emission allowances is reduced, so the carbon price is reduced. On the other hand, the government implements energy conservation and emission reduction policies. When the price of fossil energy is too high, enterprises will develop clean energy technologies, use clean energy to replace traditional energy, improve energy utilization, and reduce carbon dioxide emissions per unit capacity to reduce carbon emissions and eventually reduce carbon prices (Jiang et al. 2017; Dong et al. 2021c, 2022; Pan and Dong 2022). Based on this, we propose the following:

Hypothesis 1: The fossil energy market has a negative impact on the carbon market.

Macroeconomic development is inseparable from energy consumption, and stock prices are a barometer of economic development (Fang and Yu 2021). Macroeconomic growth, that is, the rise of stock prices, represents an increase of energy consumption and carbon dioxide emissions of various production departments, resulting in the increase of carbon emission allowance demand in the carbon trading market, while the government has restrictions on the supply of carbon emission allowances, and the carbon price rises due to the influence of the relationship between supply and demand. When economic development is blocked, carbon prices fall. The rise of stock prices, the increase of enterprise income, and the expansion of enterprises’ scale will inevitably increase the input and production of more products, increase the demand for energy, and finally lead to the rise of carbon prices. We propose:

Hypothesis 2: The stock market has a positive impact on the carbon market.

The least absolute shrinkage and selection operator model

In this paper, the LASSO model is used for variable selection. This model was first proposed by Tibshirani (1996) and has extensive use in the energy economy. The LASSO method appends the L1 regularization term into the objective function as the penalty term of the loss function to prevent overfitting of the regression model. In addition, it can also solve the problem of multicollinearity in multiple regression analysis.

\[
\hat{\beta} = \arg\min \left\{ \sum_{i=1}^{n} \left( y_i - \hat{\beta}_0 - \sum_{j=1}^{K} \hat{\beta}_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{K} |\hat{\beta}_j| \right\}, \lambda > 0
\]

where \( n \) is the number of samples and \( K \) is the number of variables in the regression model, \( \lambda \) is called the regularization parameter, which is used to control the fitting of the regression model and keep the estimated value of the parameters small. When parameter \( \lambda \) is determined, parameter \( C \) can also be determined and makes \( \sum_{j=1}^{K} |\hat{\beta}_j| = c \). When parameter \( C \) decreases gradually, some parameters \( \beta_j \) in the regression model will be reduced to 0 to achieve the purpose.
of variable selection. There are many methods to calculate the LASSO model. This paper uses the “minimum angle regression method” to calculate it.

The Markov switching vector autoregressive model

We use the MSVAR model to consider the asymmetric impact of other markets on the carbon market and the duration of the impact. The model was first proposed by Hamilton (1989) and is derived from the vector autoregressive model. The MSVAR model has the ability to switch different regimes and consider the nonlinearity of the model.

The general form of the MSVAR model considering K variables is as follows:

\[
Y_t = \begin{cases} 
C_1 + \beta_{11} Y_{t-1} + \cdots + \beta_{1p} Y_{t-p} + A_1 u_t, & \text{if } s_t = 1 \\
C_m + \beta_{1m} Y_{t-1} + \cdots + \beta_{pm} Y_{t-p} + A_m u_t, & \text{if } s_t = m 
\end{cases}
\]

It represents the probability of the \( i \) regime transition to the \( j \) regime. The probability remains stable after continuous iteration. The transition probability matrix between final regimes is expressed as follows:

\[
P = \begin{bmatrix} 
p_{11} & \cdots & p_{1m} \\
\vdots & \ddots & \vdots 
p_{1m} & \cdots & p_{mm}
\end{bmatrix}
\]

Data descriptions

This paper takes the following indicators to explore the interaction between the carbon market and other markets from a time-varying perspective. This paper selects the European Union Allowance price (EUA) as the carbon price of the carbon market. The sample time span is from January 1, 2016, to July 31, 2021. The specific variables are described in Table 1. In terms of data processing, this paper carries out first-order difference processing for T-BILL, ESTB, and ELTB, while other variables take the logarithm first, and then the yield of the variable is obtained by first-order difference processing.

Table 1 shows the descriptive statistics of the yield data. According to the standard error, the volatility of EUA is slightly higher, and the volatilities of CRB, EUR/RMB, and EUR/USD are lower. This shows that the carbon market fluctuates widely, while the commodity market and exchange

| Individual indicator | Description | Market classification | Data source |
|----------------------|-------------|-----------------------|-------------|
| EUA                  | European Union Allowance Price | Carbon market | European Climate Exchange |
| GAS                  | IPE British Natural Gas Price | Gas market | International Petroleum Exchange |
| OIL                  | IPE Brent Crude Oil Price | Oil market | International Petroleum Exchange |
| COAL                 | IPE Rotterdam Coal Price | Coal market | International Petroleum Exchange |
| T-BILL               | US 3-month treasury bill yield | Bond market | The Federal Reserve |
| JUNKBOND             | Difference between Moody’s BAA corporate bond yield and AAA corporate bond yield | Bond market | The Federal Reserve |
| ESTB                 | EU 3-month bond yield | Bond market | The European Central Bank |
| ELTB                 | EU 10-year bond yield | Bond market | The European Central Bank |
| SP500                | Standard & Poor’s 500 Index | Stock market | Wind Database |
| FSTE100              | FSTE100 Index | Stock market | Wind Database |
| DAX                  | DAX Index | Stock market | Wind Database |
| CAC40                | CAC40 Index | Stock market | Wind Database |
| CRB                  | Commodity Research Bureau Index | Commodity Market | Wind Database |
| EUR/RMB              | EUR to RMB Exchange Rate | Exchange Market | The European Central Bank |
| EUR/USD              | EUR to USD Exchange Rate | Exchange Market | The European Central Bank |
rate market are relatively stable. The above conclusion can also be confirmed through the difference between the maximum value and the minimum value. The skewness and kurtosis show that all variables have the data distribution of “peak and thin tail,” and some variable data have the characteristics of “left deviation” or “right deviation.” In other words, the distribution of each variable is different from the normal distribution.

It is easy to cause a spurious regression due to the existence of unit roots in the economic model, so the stationarity test needs to be carried out before modeling. In this paper, the two most common unit root test methods (Augmented Dickey and Fuller (1979), Phillips and Perron (1988)) are used for the stationarity test. The results in Table 3 show that under the three forms, all yield data are stationary.

Next, consider the correlation coefficient between variables. As shown in the heatmap in Fig. 3, the correlation coefficient between the relevant variables SP500, CAC40, DAX, and FSTE100 in the stock market is greater than 60%, the correlation coefficient between EUR/RMB and EUR/USD in the exchange rate market is 85%, and the correlation coefficient between other variables is relatively small.

Table 2 Descriptive statistics

|          | Mean   | Median | Max    | Min    | Std    | Skewness | Kurtosis |
|----------|--------|--------|--------|--------|--------|----------|----------|
| EUA      | 0.0014 | 0.0018 | 0.186  | -0.195 | 0.032  | -0.418   | 7.818    |
| GAS      | 0.0008 | 0.0004 | 0.343  | -0.173 | 0.037  | 0.881    | 10.918   |
| OIL      | 0.0006 | 0.0023 | 0.191  | -0.280 | 0.027  | -1.189   | 23.091   |
| COAL     | 0.0008 | 0.0000 | 0.194  | -0.181 | 0.018  | 0.443    | 37.545   |
| JUNKBOND | 0.0001 | 0.0000 | 0.100  | -0.128 | 0.010  | -0.421   | 39.280   |
| T-BILL   | -0.0001 | 0.0000 | 0.110  | -0.230 | 0.024  | -1.919   | 20.043   |
| SP500    | 0.0006 | 0.0008 | 0.090  | -0.128 | 0.012  | -1.200   | 24.917   |
| CAC40    | 0.0003 | 0.0007 | 0.081  | -0.131 | 0.013  | -1.295   | 18.262   |
| DAX      | 0.0003 | 0.0008 | 0.014  | -0.131 | 0.013  | -0.974   | 17.329   |
| FST100   | 0.0001 | 0.0000 | 0.087  | -0.115 | 0.011  | -1.063   | 17.998   |
| CRB      | 0.0003 | 0.0002 | 0.020  | -0.023 | 0.004  | -0.026   | 6.689    |
| ESTB     | -0.0002 | 0.0008 | 0.176  | -0.088 | 0.017  | 2.311    | 23.183   |
| ELTB     | -0.0009 | -0.0021 | 0.186  | -0.141 | 0.032  | 0.360    | 5.468    |
| EUR/USD  | 0.0001 | 0.0001 | 0.025  | -0.029 | 0.005  | 0.113    | 5.836    |
| EUR/RMB  | 0.0001 | -0.0001 | 0.024  | -0.022 | 0.004  | 0.202    | 6.062    |

Table 3 Unit root tests

| Variables | Augmented Dickey-Fuller | Philips-Perron | Stationary |
|-----------|-------------------------|----------------|------------|
|           | \( I \) | \( T&I \) | \( N \) | \( I \) | \( T&I \) |          |
| EUA       | -39.11 | -39.18 | -39.21 | -39.11 | -39.13 | -39.16 | Y         |
| GAS       | -33.96 | -33.97 | -33.98 | -33.89 | -33.89 | -33.90 | Y         |
| OIL       | -35.15 | -35.15 | -35.14 | -35.22 | -35.22 | -35.21 | Y         |
| COAL      | -36.25 | -36.31 | -36.31 | -36.26 | -36.31 | -36.31 | Y         |
| JUNKBOND  | -18.18 | -18.17 | -18.17 | -45.61 | -45.60 | -45.58 | Y         |
| T-BILL    | -10.99 | -10.98 | -11.15 | -34.69 | -34.69 | -34.41 | Y         |
| SP500     | -11.34 | -11.55 | -11.54 | -45.25 | -45.52 | -45.52 | Y         |
| CAC40     | -35.73 | -35.74 | -35.73 | -35.78 | -35.78 | -35.78 | Y         |
| DAX       | -36.35 | -36.36 | -36.34 | -36.39 | -36.39 | -36.38 | Y         |
| FST100    | -36.96 | -36.95 | -36.94 | -36.96 | -36.95 | -36.94 | Y         |
| CRB       | -31.66 | -31.82 | -31.90 | -34.38 | -34.13 | -34.06 | Y         |
| ESTB      | -41.56 | -41.55 | -41.54 | -41.54 | -41.54 | -41.50 | Y         |
| ELTB      | -34.66 | -34.67 | -34.66 | -34.62 | -34.64 | -34.63 | Y         |
| EUR/USD   | -37.05 | -37.04 | -37.03 | -37.07 | -37.06 | -37.05 | Y         |
| EUR/RMB   | -38.60 | -38.59 | -38.60 | -39.07 | -39.07 | -39.18 | Y         |

Y means stationary series and N means nonstationary series. All data were statistically significant at the 1% level.
low, indicating that the correlation between the yield series is weak. From the perspective of the explained variable EUA, the correlation coefficient between EUA and its explanatory variables from the energy market and stock market is higher than 20%, while the correlation coefficient between other explanatory variables and EUA is lower than 10%. Therefore, it is preliminarily inferred that the fluctuation of the carbon market is mainly affected by the energy market and stock market.

**Empirical results and discussion**

**Variable selection**

In this section, we show the results of variable selection. Before variable selection, this paper uses “min–max normalization” to perform a linear transformation on the data to eliminate the influence of the order of the variables on the parameters of the regression model. The formula is as follows:

\[
y_i = \frac{x_i - \min\{x_j\}_{1 \leq j \leq n}}{\max\{x_j\}_{1 \leq j \leq n} - \min\{x_j\}_{1 \leq j \leq n}}
\]

\(x_i\) is the original data, and \(y_i\) is the data after processing.

Figure 4 shows that the model selects fewer prediction variables from May 2018 to March 2019, approximately two were selected. In other time periods, from August 2017 to May 2018 and from March 2020 to July 2021, approximately 8 variables were selected. Affected by EU policies, carbon prices began to show an increasing trend in 2018, while energy factors and macroeconomic factors also showed increasing trends. The LASSO model tends to choose the factors with greater impact. After the structural break, energy factors and macroeconomic factors fluctuate greatly, causing EUA to fluctuate violently. A large fluctuation means that the trend changes greatly, which also creates variable selection diversity.

To further illustrate the selection of variables at different time points of the LASSO model, Fig. 5 shows the selected (discarded) variables at each point in time are displayed in.
dark blue (white). The relevant variables of the exchange rate market and the bond market are usually selected in the early stage, while the relevant variables of the stock market are selected many times in the later stage. The variables of the energy market run through the whole period, reflecting the close relationship between the energy market and the carbon market. Taking into account the situation before and during COVID-19, we will take the top four variables, i.e., GAS (100%) and OIL (75.5%), COAL (41.3%), and DAX (47.3%), as the key determinants, consider their relationship with carbon prices, and analyze the interaction between markets. In addition, according to the
correlation coefficient, FSTE100, DAX, and CAC40 have strong correlations but they are not selected by the model, which shows that LASSO can solve the multicollinearity problem well.

To evaluate the quality of the indicators selected by LASSO, this paper applies the prediction model for verification. In this paper, the autoregressive comprehensive moving average model (ARIMA), support vector regression (SVR), and kernel ridge regression (KRR) are selected as the prediction benchmark models. The parameters $p$ and $Q$ in the ARIMA model are automatically determined by the model. In addition, the kernel function parameters of the SVR and KRR models are set to $\alpha = 0.1$. In this paper, the mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE) are used as the evaluation indices of the prediction model to evaluate the prediction capability of the model. The formula is as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |r_i - \hat{r}_i|$$  \hspace{1cm} (6)

$$MSE = \frac{1}{n} \sum_{i=1}^{n} |r_i - \hat{r}_i|^2$$  \hspace{1cm} (7)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|r_i - \hat{r}_i|}{r_i}$$  \hspace{1cm} (8)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (r_i - \hat{r}_i)^2}$$  \hspace{1cm} (9)

Table 4 shows that the SVR, KRR, and LASSO models can effectively predict the trend of EUA yield. Although ARIMA has good prediction ability in price data, it does not perform well in the prediction of yield data. The MAPE of each model is higher because there is an abnormal point in March 2020, and the model cannot predict it well. However, from the perspective of prediction indicators, the LASSO model has smaller MAE and RMSE than the other models, so LASSO has higher prediction accuracy, indicating that it can also select better prediction variables.

### Analysis of the impact of the energy and financial markets on the carbon market

To study the relationship between variables, we need to estimate a VAR model first. In this paper, the final prediction error, the minimum Schwarz information criterion (SC), Akaike information criterion (AIC), and Hannan Quinn information criterion (HQ) are used as evaluation indexes to determine the optimal lag order of VAR model estimation. Table 5 shows that the optimal lag order of the VAR model is 1.

After the estimation of the VAR model, the BDS method is used to judge whether there is a nonlinear correlation in the residuals. Table 6 shows the rejection of the assumption that a linear correlation appears in variables at a significance level of 1%; that is, there is an obvious nonlinear correlation between variables.

In this paper, the MSVAR model is used to consider the nonlinear relationship between variables to show the possible structural break and regime changes. The MSVAR model has different forms, mainly reflected in the changes in intercept, coefficient, and residual. The form of the MSVAR

### Table 4 Forecasting performance

| Forecasting models | MAE(%) | MSE(%) | MAPE(%) | RMSE(%) |
|--------------------|--------|--------|---------|---------|
| LASSO              | 5.17   | 0.49   | 13.51   | 7.02    |
| SVR                | 5.24   | 0.50   | 13.56   | 7.09    |
| KRR                | 5.34   | 0.53   | 13.65   | 7.27    |
| NAVIE              | 9.43   | 1.53   | 21.03   | 12.36   |
| ARIMA              | 6.26   | 0.74   | 16.15   | 8.59    |

### Table 5 VAR lag selection

| Lag length | 0   | 1*  | 2   | 3   | 4   |
|------------|-----|-----|-----|-----|-----|
| Log L      | 15,682.39 | 15,725.60 | 15,744.79 | 15,770.24 | 15,792.08 |
| LR         | NA  | 86.03 | 38.05 | 50.30 | 42.98* |
| FPE        | 3.90E-17 | 3.80E-17*| 3.83E-17 | 3.83E-17 | 3.85E-17 |
| AIC        | −23.59 | −23.62*| −23.61 | −23.61 | −23.61 |
| SC         | −23.57* | −23.50 | −23.40 | −23.30 | −23.20 |
| HQ         | −23.59* | −23.58 | −23.53 | −23.50 | −23.45 |

* indicates lag order selected by the criterion

LR sequential modified LR test statistic (each test at 5% level), FPE final prediction error, AIC Akaike information criterion, SC Schwarz information criterion, HQ Hannan-Quinn information criterion

### Table 6 Results of BDS test from the VAR residuals of all variables

| Embedding dimension(m) | 2   | 3   | 4   | 5   | 6   |
|------------------------|-----|-----|-----|-----|-----|
| EUA                    | 0.0138 | (0.0022) | 0.0287 | (0.0035) | 0.0382 | (0.0042) | 0.0438 | (0.0044) | 0.0447 | (0.0042) |
| GAS                    | 0.0204 | (0.0024) | 0.0411 | (0.0039) | 0.0550 | (0.0046) | 0.0646 | (0.0048) | 0.0704 | (0.0046) |
| OIL                    | 0.0294 | (0.0027) | 0.0534 | (0.0042) | 0.0684 | (0.0050) | 0.0755 | (0.0053) | 0.0786 | (0.0051) |
| COAL                   | 0.0250 | (0.0031) | 0.0484 | (0.0049) | 0.0631 | (0.0058) | 0.0681 | (0.0061) | 0.0677 | (0.0059) |
| DAX                    | 0.0199 | (0.0026) | 0.0423 | (0.0042) | 0.0605 | (0.0050) | 0.0698 | (0.0052) | 0.0721 | (0.0050) |

All data were statistically significant at the 1% level
model needs to be set before modeling. According to the lag criterion of the VAR model, log likelihood (LL), and likelihood ratio (LR) indicators, this paper finally constructs the MSAH(2)-VAR(1) model. According to the estimation results of MSVAR, the original hypothesis of the linear model is rejected at a 1% significance level, indicating that the MSVAR model can analyze the nonlinear relationship between the carbon market and other markets.

Table 7 shows the estimation results of the MSVAR model parameters, in which the estimated standard error of regime 1 and regime 2 is showing that EUA is 0.027 and 0.048, GAS is 0.028 and 0.060, OIL is 0.018 and 0.049, COAL is 0.008 and 0.036, and DAX is 0.009 and 0.022, respectively. The volatility of each variable in regime 2 is significantly higher than that in regime 1. In addition, according to the smoothing probability in Fig. 6, it can also be confirmed that the period of regime 2 is often the period of severe fluctuation of carbon price returns, and regime 1 is the period of relatively gentle fluctuation of carbon price returns. Therefore, this paper defines the period of regime 1 as the period of low volatility and the period of regime 2 as the period of high volatility.

The coefficient is not significant in the model estimation for the high volatility period, which may be caused by an insufficient sample size in the high volatility period. The low volatility period and high volatility period account for 80.13% and 19.87% of the samples, respectively. The transition probability between regimes is shown in Table 7. The probability of maintaining a low volatility regime is 0.877, while the probability of a regime transition is 0.123.
indicating that the low volatility regime is relatively stable; the probability of maintaining high volatility is 0.504, and the probability of a transition from a high volatility regime to a low volatility regime is 0.496, indicating that the high volatility regime is not very stable. In addition, Table 7 also shows the duration of each regime, in which the low volatility regime lasts for an average of 8 days and the high volatility regime lasts for an average of 2 days. Figure 6 b more intuitively shows that in the period of low volatility, EUA tends to produce low fluctuations, while Fig. 6 c shows that the high fluctuation regime of EUA is not stationary.

Table 8 shows the estimation results of the carbon price fluctuation equation under different time spans. It can be seen from the table that under the period of low volatility, the energy market has a negative impact on the carbon market in different sample periods, while the stock market has a positive impact on the carbon market. Under the period high volatility, the oil market has a positive impact on the carbon market, while the stock market has a negative impact on the carbon market. From the estimation results of the carbon price fluctuation equation, we know that the intensity and direction of the impact relationship between markets are basically robust under different sample periods. The impact of energy markets and stock markets on the carbon market is unlikely to be accidental.

Table 8: Estimation results under different samples

| Simple period | 2016/1–2021/7 | 2017/1–2021/7 | 2018/1–2021/7 |
|---------------|---------------|---------------|---------------|
|               | Regime 1      | Regime 2      | Regime 1      | Regime 2      | Regime 1      | Regime 2      |
| Constant      | $EUA_t$       | $EUA_t$       | $EUA_t$       | $EUA_t$       | $EUA_t$       | $EUA_t$       |
|               | 0.002***      | 0.002***      | 0.003***      | 0.003***      | 0.003***      | 0.003***      |
|               | (0.001)       | (0.001)       | (0.001)       | (0.001)       | (0.001)       | (0.001)       |
| $EUA_{t-1}$   | -0.020        | -0.082        | -0.040        | -0.057        | -0.032        | 0.220         |
|               | (0.033)       | (0.092)       | (0.036)       | (0.106)       | (0.039)       | (0.134)       |
| $GAS_{t-1}$   | -0.046*       | -0.025        | -0.048*       | 0.002         | -0.053*       | -0.042        |
|               | (0.027)       | (0.072)       | (0.027)       | (0.075)       | (0.029)       | (0.076)       |
| $OIL_{t-1}$   | -0.135***     | 0.038         | -0.134***     | 0.085         | -0.125***     | 0.088         |
|               | (0.041)       | (0.081)       | (0.045)       | (0.083)       | (0.044)       | (0.090)       |
| $COAL_{t-1}$  | -0.066        | -0.089        | -0.083        | -0.147        | -0.061        | -0.074        |
|               | (0.081)       | (0.116)       | (0.073)       | (0.118)       | (0.081)       | (0.127)       |
| $DAX_{t-1}$   | -0.083        | -0.013        | 0.141         | -0.181        | 0.188**       | -0.590**      |
|               | (0.092)       | (0.194)       | (0.093)       | (0.213)       | (0.089)       | (0.278)       |
The analyses of cumulative impulse responses

To study the interaction between macroeconomic factors, energy factors, and the carbon market, this paper uses the cumulative impulse response method to discuss the short-term dynamic shock of various factors on the carbon market. The cumulative impulse response method considers the cumulative responses of EUA to GAS, OIL, COAL, and DAX stock price shocks. The direction and intensity of the impact of economic and energy factors on EUA within 7 days are considered in this paper, as shown in Fig. 7.

First, we discuss the dynamic shock of the natural gas market on the carbon market in the energy market, as shown in Fig. 7 a. In the period of low volatility, the shock of the current EUA on GAS shows a negative response, and the negative response is $-0.0461$. On the second day, the negative response of the EUA to gas weakens and finally stabilizes at $-0.0461$; in the period of high volatility, the shock of the current EUA on gas still shows a negative response, but the negative response increases on the second day and then weakens slightly in the next two days. Finally, it remained stable on the fifth day. Generally, whether in periods of high volatility or low volatility, the shock of the natural gas market on the carbon market is negative, but the negative shock of the natural gas market is stronger in periods of low volatility.

Second, the dynamic shock of the oil market on the carbon market is discussed in Fig. 7 b. In the period of low fluctuation, the shock of the current EUA on OIL shows a negative response, the negative response is $-0.1356$, and the negative response remains stable the next day. In the period of high volatility, the shock of the current EUA on OIL shows the opposite positive response, shows a gradually increasing trend, and finally stabilizes at $0.0487$ on the fifth day. Obviously, the direction and size of the shock of the oil market on the carbon market under different systems have changed. In addition, the negative shock of the oil market is stronger in periods of low volatility.

Next, considering the dynamic shock of the coal market on the carbon market through Fig. 7 c, in the period of low volatility, the shock of the current EUA on COAL shows a negative response, and the negative response gradually

Fig. 7 Cumulative impulse responses of EUA. a Cumulative impulse responses of EUA to GAS. b Cumulative impulse responses of EUA to OIL. c Cumulative impulse responses of EUA to COAL. d Cumulative impulse responses of EUA to DAX
increases. On the fourth day, the negative response tends to be stable, and the negative response reaches $-0.0765$. In the period of high volatility, the shock of the current EUA on coal is a negative response, and then the negative response weakens to a certain extent, tends to be stable on the third day, and the negative response is $-0.0790$. The coal market has a negative shock on the carbon market in different periods. However, different from the natural gas market and oil market, the negative shock of the coal market is stronger in periods of high volatility.

Finally, considering the dynamic shock of the stock market on the carbon market, it can be seen from Fig. 7d that in the period of low volatility, the shock of the current EUA on DAX has a positive response, and the positive response is 0.0888. The positive response weakens the next day and finally tends to be stable. In the period of high volatility, the shock of the current EUA on DAX is a negative response, and the negative response is $-0.0132$. Then, the positive response weakens to a certain extent, fluctuates slightly, and tends to gradually stabilize. We find that the shock of the European stock market on the carbon market is different in both size and direction. The shock of the European stock market on the carbon market is stronger in periods of high volatility. The shock response of the carbon market to the energy market and stock market has perceptible time-varying characteristics. The impact response of the carbon market to the energy market and stock market in different periods is different in both intensity and direction.

The research found that the maximum response of EUA to the impact of GAS, OIL, and COAL is $-0.0461$, $-0.1356$, and $-0.0888$, respectively, indicating that the shock of the oil market on the carbon market is stronger than that of the natural gas market and coal market. In the period of low volatility, the impact of the three fossil energy markets on the carbon market is a negative effect, which confirms Hypothesis 1. The price of fossil energy will have a negative impact on the carbon market because it affects the production cost of enterprises and the energy structure. The impact of the stock market on the carbon market is a positive effect, which confirms Hypothesis 2. The stock price will affect the enterprise production scale and energy consumption and have a positive impact on the carbon market. In a period of high volatility, when major events occur, such as an epidemic, macromacroeconomic activities are impacted, the production capacity of enterprises decreases, the energy demand decreases, and the oil price is the first to be impacted and fall, while the carbon price also decreases due to the obstruction of production activities, resulting in a decline in carbon emission allowance demand, resulting in the decline of the carbon price. At these times, the oil market has a short-term positive effect on the carbon price.

Economic and financial development will have a short-term or long-term impact on carbon dioxide emissions (Khan et al., 2020). This is because there is a strong correlation among the economy, energy, and environment. Faster economic development leads to increased energy consumption, resulting in more carbon emissions. Koch et al. (2014) and Lin and Jia (2019) show that when the carbon price is low, an economic stimulus policy cannot work and will not achieve the goal of carbon emission reduction. Therefore, it is more feasible to increase the carbon price and force enterprises to save energy and reduce carbon emissions. The energy price will affect the carbon price to some extent but it is unrealistic to increase the carbon price by adjusting the energy price. A carbon pricing mechanism should be considered to increase carbon prices from the perspective of supply and demand. The European Commission reformed the EU carbon emission trading system, promulgated the market stability reserve (MSR) policy, recovered the excess carbon allowance in the market, and increased the annual linear reduction factor (LRF) of the emission cap to reduce the supply of annual carbon allowance (Bruninx et al. (2020) and Hu et al. (2015)). At the beginning of 2018, the price of EUA was lower than 10 euros/ton of carbon dioxide. After the reform, the price of EUA gradually increased.

In view of the rising carbon price, enterprises should implement technological innovations, improve their energy utilization, and adjust their energy structure. Countries all over the world should also consider renewable energy and increase their clean energy use proportions (Wu et al. 2020; Gong et al. 2021; Li et al. 2020). As shown in Fig. 8, greenhouse gas (GHG) emissions mainly come from energy consumption. In 2018, energy consumption accounted for 76% of the total greenhouse gas emissions, of which power generation and heating accounted for 31%. From Fig. 9, it can be seen that there are huge structural differences in the power generation energy consumption between the world and the EU, which shows, proportionally, the world uses much more coal than the EU. The largest power generation energy consumption in the world is through coal, while the EU consumes more clean energy. The proportion of clean energy power generation in the EU is significantly higher, which also leads to relatively low total carbon emissions in the EU. Therefore, to control carbon emissions, all countries should appropriately adjust the energy structure of their power generation infrastructure. Of course, not only the power industry but also other high-energy consuming industries should appropriately adjust their energy structures and turn to clean energy.
Conclusions and policy implications

Conclusion

An exploration of the impact mechanisms of carbon prices is beneficial for governments and enterprises in making decisions. It is prudent to examine the role of carbon pricing to more effectively achieve emission reduction targets and to protect the environment. This paper uses the MSVAR model to consider the impact of macroeconomic factors and energy factors on the carbon market’s volatility and analyzes the time-varying characteristics of the factors and market differences.
Based on the daily EUA price data from January 2016 to July 2021, a nonlinear empirical analysis was conducted. Before the empirical analysis, the LASSO model was used to select the variables and the most relevant indicators of the carbon market. We can draw the following conclusions from the study.

(1) First, the variables of relevant factors were selected through the LASSO model, and the time variability of the influencing factors was considered. The results show that GAS, Oil, COAL, and DAX are the key determinants of carbon prices. In addition, energy factors are the long-term influencing factors of carbon market fluctuations, and economic factors have a short-term impact on the carbon market.

(2) To better study the time-varying characteristics and market heterogeneity between the carbon market and other markets, we used the MSVAR model for an empirical analysis. The results show that the carbon price fluctuations are marked by dynamic changes of “high fluctuation” and “low fluctuation.” The carbon price was in a low fluctuation state for a long time and a high fluctuation state for a short time, and the high fluctuation state was not stable. The energy market had a negative effect on the carbon market, and the stock market had a positive effect on the carbon market.

(3) Through an impulse response analysis, we know that there are differences in the intensity and duration of the impact of various factors on carbon prices. In the energy market, in the period of low fluctuation, the impact of the oil market on the carbon market was stronger than that of the natural gas market and coal market. In the period of high volatility, the coal market had a stronger impact on the carbon market. The response duration of the carbon market to various factors was relatively short.

**Policy implications**

The above conclusions motivate the following suggestions to governments and enterprises in making carbon emission reduction decisions.

(1) The energy market is closely related to the carbon market and has a negative effect on it. However, it is unreasonable to reduce the carbon emissions of enterprises by increasing the price of fossil energy because the energy market price is mainly determined by supply and demand. The government should start with a supply of carbon emission allowances, reduce the discretionary carbon emission allowances, increase the carbon emission costs of polluting enterprises, and encourage polluting enterprises to carry out technological transformations in energy conservation and emission reduction. In addition, relevant preferential policies can be given to clean energy enterprises, such as bank loan interest rate reductions, to encourage enterprises to reduce carbon emissions and to ultimately achieve carbon neutralization at the national level.

(2) Enterprises need to pay attention to relevant EU policies in advance to avoid the risks brought by rising carbon prices. Enterprises should increase the proportion of clean energy power generation, optimize the energy structure, switch to renewable energy, and implement low-carbon emission policies. Enterprises also need to pay attention to training their talent, strengthening research and development, accelerating the marketization of green and safe technologies, improving energy utilization, and maximizing the use of their resources to generate benefits.

(3) Investors use the long-term and short-term impacts of energy factors and stock factors on the carbon market to make reasonable investments in carbon financial products. Investors need to pay attention to policy changes, understand the changes in energy prices and the development direction of the stock market in advance, and use known remedies to avoid risks. In the context of carbon peaking and carbon neutralization, investments in clean energy enterprises is a necessity.

The transmission relationship between markets was analyzed on the basis of price information. In fact, carbon market pricing needs to consider many aspects, not only supply and demand but also policies. For example, in terms of influencing factors, carbon emissions are also affected by weather and temperature. Owing to the different technological levels and carbon emission stages in various countries, future research needs to advance specific suggestions for each country in combination with macroeconomic environmental policies.

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