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Exploring the Linkage Effects between Coking Coal Futures and Carbon Emission Rights Prices under the Dual-Carbon Framework

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Abstract

Coking coal is a vital energy resource for economic development, with fluctuations in coking coal futures prices significantly guiding spot prices. Additionally, variations in carbon emission rights prices directly affect China's energy conservation and emission reduction efforts. This paper examines the daily trading prices of carbon emission rights and coking coal futures. It utilizes various tests, including the ADF test and cointegration test, and constructs a two-dimensional vector autoregression (VAR) model with a two-period lag. The paper also performs an impulse response function analysis and variance decomposition. Empirical results reveal: First, the daily trading prices of coking coal futures have exhibited a fluctuating upward trend over the past six years; Second, there is a long-term cointegration relationship between coking coal futures prices and carbon emission rights prices; Third, there is no Granger causality between the two; Fourth, fluctuations in carbon emission rights prices have a stronger guiding effect on coking coal futures prices than vice versa. Recommendations include: (1) Strengthening oversight of the coking coal futures market and leveraging policy guidance to prevent extreme prices; (2) Systematically including more participants in the carbon market, optimizing the trading structure, and promoting healthy market development; (3) When developing policies for carbon emission rights, the government should mitigate the impact of price fluctuations on other sectors.

Keywords: Cointegration Test; Impulse Response Function; VAR Model; Energy Market Linkage

1. Introduction

The sharp rise in carbon emissions has led to severe environmental problems and hindered sustainable development. From the United Nations Framework Convention on Climate Change in 1992, the Kyoto Protocol in 1997, to the Paris Agreement in 2016, countries have made significant strategic adjustments to address climate change proactively. Other nations have long utilized market mechanisms for energy conservation and emission reduction, achieving notable results. China's carbon market began later, with the first carbon spot trading in Shenzhen in 2013, followed by the launch of the national carbon market for the power sector in 2017, initially focusing on regional markets. With the proposal of the "3060 dual-carbon goals" in 2020, China's carbon trading market officially launched on July 16, 2021. The 2022 report of the 20th National Congress further emphasized "actively and steadily promoting carbon peaking and carbon neutrality." The development of China's carbon futures market has since accelerated, laying a solid foundation for market-based energy conservation and emission reduction. By 2023, the carbon price had increased by 23% compared to 2022, and the trading volume had quadrupled. Before the launch of the carbon market, most academic research focused on European carbon futures and China's regional carbon spot markets. Since the market launch, studies have primarily examined the emission reduction and welfare effects brought by the carbon market. As a core component of the coking, coal, and steel industrial chain, coking coal holds a crucial position. Investigating the causal relationship between domestic coking coal futures prices and carbon emission rights prices, and understanding their interaction mechanisms, provides valuable insights for promoting the healthy development of China's carbon market. This study also offers policy guidance and empirical references for formulating low-carbon policies and optimizing energy conservation and emission reduction strategies.

2. Literature Review and Commentary

2.1 Literature Review

As economic development progresses, the links between energy markets and international energy markets have become increasingly tight, making it essential to explore the linkage effects between energy prices. Warell (2006) found no long-term cointegration relationship in international steam coal prices in the 1990s. Wei Weixian et al. (2007) quantitatively analyzed domestic and international crude oil prices, finding volatility spillover between them and that international oil prices had a decisive guiding effect on domestic oil prices. Bentzen (2007) studied the linkages among OPEC crude oil prices, Brent, and WTI crude oil prices, discovering bidirectional Granger causality among them. Ma Chaoqun (2009) found information spillover effects among WTI crude oil prices, Singapore fuel oil prices, and Shanghai fuel oil prices.

Regarding coal prices and carbon emission rights, Yi Lan et al. (2017) used the MIV-BP neural network model and found that coal prices had a greater impact than crude oil prices, and crude oil prices had a greater impact than natural gas prices. Xue et al. (2017) found a long-term cointegration relationship and bidirectional Granger causality between foreign coal prices and domestic coal prices using the MSVEC model. Yan Zheming et al. (2017) found that the energy structure is a critical transmission channel for the effectiveness of carbon emission rights trading price policies. Liu Junyang et al. (2020) found a positive correlation between coal prices and carbon emission rights trading prices using a GARCH-MIDAS model. Zhao Lingdi et al. (2021) found a bidirectional spillover effect between China's energy market and the carbon emission rights trading market based on the spillover index model. Wei Yu et al. (2022) found that the impact of international energy prices on China's carbon emission rights trading prices has gradually declined. In summary, domestic and international scholars have employed various research methods to study energy markets, including Johansen cointegration tests, Granger causality tests, VAR models, and GARCH models. The research primarily focuses on the cointegration relationships, causality, and spillover effects between energy prices. However, there is limited research on the linkage effects between coking coal futures prices and carbon emission rights prices. This paper uses ADF tests, cointegration tests, VAR models, impulse response function analysis, and variance decomposition to explore the dynamic effects of coking coal futures prices and carbon emission rights prices within the dual-carbon context.

2.2 Literature Commentary

A review of previous literature reveals several gaps: First, the limited operational period of China's carbon trading market has led to a scarcity of relevant studies. Second, the mechanism by which coking coal price fluctuations affect carbon emission rights prices, given its critical role in the coking coal-steel industry chain, remains undefined. This paper aims to fill these research gaps by using a range of empirical methods to deeply analyze the dynamic relationship between coking coal futures prices and carbon emission rights prices, providing theoretical support and policy recommendations for the healthy development of China's carbon market.

3. Theoretical Model

Yang Sheng and He Lingyun (2008) observed that time series data are typically non-stationary. Thus, using ordinary least squares for empirical analysis in time series research has notable limitations, as it cannot test the equilibrium relationship of non-stationary time series. Engle and Granger introduced cointegration theory and the vector error correction model to assess the long-term equilibrium of non-stationary time series. This paper employs empirical methods such as the ADF unit root test, Johansen cointegration test, Granger causality test, VAR structural vector autoregression model, impulse response function, and variance decomposition. The study uses daily trading price data of coking coal futures from the Dalian Commodity Exchange and carbon emission rights prices from the China Emissions Exchange, converting these variables into logarithmic series. The optimal lag period is selected to construct a two-dimensional VAR model. Based on the impulse response analysis and variance decomposition method of the VAR model, the paper explores the relationship between coking coal futures prices and carbon emission rights prices under the dual-carbon framework.

3.1 Unit Root Test (ADF Test)

Stationary data series are prerequisites for a long-term cointegration relationship. Therefore, it is crucial to test the stationarity of the time series before investigating the long-term cointegration relationship of variables. The null hypothesis is set as H_0: ρ=1 or ρ-1=0, which indicates the time series is non-stationary and has a unit root. The augmented Dickey-Fuller (ADF) model is then employed for testing, comparing the test value of the original model with the critical value. If the absolute value of the test statistic is greater than the absolute value of the critical value, the null hypothesis is rejected, indicating the data series is stationary and free of a unit root.

Model (1), without intercept and trend term:

$$\Delta x_t = (\rho - 1)x_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta x_{t-i} + \phi_t \tag{1}$$

Model (2), with an intercept included but without a trend term:

$$\Delta x_t = \alpha + (\rho - 1)x_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta x_{t-i} + \phi_t \tag{2}$$

Model (3), with both intercept and trend term included:

$$\Delta x_t = \alpha + \beta \mathrm{t} + (\rho - 1)x_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta x_{t-i} + \phi_t \tag{3}$$

3.2 Cointegration Test (Johansen Test)

Following the unit root test, the cointegration test is applied to further investigate the existence of a long-term cointegration relationship between the two variables. This study uses the Engle-Granger two-step method, with the following specific steps: Step one:

Apply the ordinary least squares (OLS) model, with the formula as follows:

$$y_t = \beta_1 + \beta_2 x_t + \varepsilon_t \tag{4}$$

When ε_t meets the relevant requirements of OLS, the residual sequence expression can be further written as:

$$\mathrm{e}_t = y_t - (\hat{\beta}_1 + \hat{\beta}_2 x_t) \tag{5}$$

Step two: Continue using the unit root test to verify whether the residual sequence is stationary. If the null hypothesis is rejected, it indicates that the residual sequence is stationary, confirming a long-term cointegration relationship between y_t and x_t.

3.3 VAR Model Construction

This study examines coking coal futures data and carbon emission rights trading data, both of which are financial time series data with complex correlations, rather than a simple unidirectional relationship where one variable influences another. Therefore, a Vector Autoregression (VAR) model is utilized for measurement. The VAR model is an unstructured model that formulates equations using the statistical characteristics of the data itself and the lag functions of the variables. This study constructs a multivariate time series vector autoregression model. Two sets of time series, $\{y_{1t}, y_{2t}\}$, are used as the dependent variables in the regression equations, with the explanatory variables being the p-order lagged regression values of these two variables. A bivariate VAR(p) system is constructed, followed by a Granger causality test to determine whether the two variables are "Granger causes" of each other:

$$\begin{cases} \mathrm{y}_{1\mathrm{t}} = \beta_{10} + \beta_{11} y_{1,t-1} + \cdots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{2,t-1} + \cdots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2\mathrm{t}} = \beta_{20} + \beta_{21} y_{1,t-1} + \cdots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{cases} \tag{6}$$

where $\{\varepsilon_{1t}\}$ and $\{\varepsilon_{2t}\}$ are both white noise, implying no autocorrelation within each series, but "contemporaneous correlation" between them is allowed;

$$Cov(\varepsilon_{1t}, \varepsilon_{2t}) = \begin{cases} \sigma_{12}, & t = s \\ 0, & \text{others} \end{cases}$$

Since the explanatory variables in the two equations of formula (6) are the same, the equations can be further simplified as follows:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} \\ \beta_{21} \end{pmatrix} y_{1,t-1} + \cdots + \begin{pmatrix} \beta_{1p} \\ \beta_{2p} \end{pmatrix} y_{1,t-p} + \begin{pmatrix} \gamma_{11} \\ \gamma_{21} \end{pmatrix} y_{2,t-1} + \cdots + \begin{pmatrix} \gamma_{1p} \\ \gamma_{2p} \end{pmatrix} y_{2,t-p} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2} \end{pmatrix}$$

By combining the coefficients, the matrix formula is derived as follows:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2} \end{pmatrix}$$

Let $\vec{y}_t \equiv \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}, \vec{\varepsilon}_t \equiv \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$, we obtain：

$$\vec{y}_t = \underbrace{\begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix}}_{\Gamma_0} + \underbrace{\begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix}}_{\Gamma_1} \vec{y}_{t-1} + \cdots + \underbrace{\begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix}}_{\Gamma p} \vec{y}_{t-p} + \vec{\varepsilon}_t$$

Define the corresponding coefficient matrix as$\Gamma 0$， $\Gamma 1$， …Γp we obtain:

$$\vec{y}_t = \vec{\Gamma}_0 + \vec{\Gamma}_1 \vec{y}_{t-1} + \cdots + \vec{\Gamma}_p \vec{y}_{t-p} + \vec{\varepsilon}_t \tag{7}$$

3.4 Impulse Response Function and Variance Decomposition

The impact of a one standard deviation shock on the study variables is often referred to as the impulse response function, which utilizes the shock path to reflect the dynamic relationship between variables. The VAR model constructed in this paper includes two variables. The VAR(p) model can further be expressed as a "vector moving average process" VAR(∞):

$$\vec{y}_t = \vec{\alpha} + \vec{\varepsilon}_t + \vec{\Psi}_1 \vec{\varepsilon}_{t-1} + \vec{\Psi}_2 \vec{\varepsilon}_{t-2} + \cdots = \vec{\alpha} \sum_{i=0}^{\infty} \vec{\Psi}_i \vec{\varepsilon}_{t-i} \tag{8}$$

The partial derivative of the two-dimensional vector y_{t+s} with respect to the two-dimensional vector ε_t' yields the 2×2 matrix Ψ_s:

$$\frac{\partial \vec{y}_{t+s}}{\partial \vec{\varepsilon}_t'} = \vec{\Psi}_s = \begin{pmatrix} \dfrac{\partial y_{1,t+s}}{\partial \varepsilon_{1t}} & \dfrac{\partial y_{1,t+s}}{\partial \varepsilon_{2t}} \\ \dfrac{\partial y_{2,t+s}}{\partial \varepsilon_{1t}} & \dfrac{\partial y_{2,t+s}}{\partial \varepsilon_{2t}} \end{pmatrix} \tag{9}$$

$\partial y_{i,t+s} / \partial \varepsilon_{jt}$ indicates the effect on the value of the i-th variable $y_{i,t+s}$ when the disturbance term ε_{jt} of the j-th variable increases by 1 unit in period t. The impulse response function can be used to analyze the strength and duration of the impact of carbon emission rights price changes in the carbon trading market on coking coal futures prices in the futures market.

The basic principle of variance decomposition involves breaking down each endogenous variable in the system into components associated with the error terms of each equation, thus examining the significance of these error terms to the endogenous explanatory variables in the model. This study employs variance decomposition to investigate the contribution rate of carbon emission rights prices to coking coal futures prices.

4. Econometric Model and Data Description

4.1 Data Selection and Processing

4.1.1 Coking Coal Futures Prices

To ensure the continuity and representativeness of the data, this paper selects the "Coking Coal Main Continuous" contract prices from the Dalian Commodity Exchange as the variable, with the data sourced from Tonghuashun Futures. Since China proposed the goals of "carbon peaking" by 2030 and "carbon neutrality" by 2060 in September 2020, this study uses daily trading data from January 2, 2018, to February 21, 2024, as the initial dataset (Group A), totaling 1,488 trading days. Given that the carbon trading market officially launched on July 16, 2021, to ensure consistency between the coking coal futures price data and the carbon emission rights trading price data, this paper further selects the daily closing prices from July 16, 2021, to February 21, 2024, as the variable (Group B), totaling 269 trading days.

4.1.2 Carbon Trading Prices

China's carbon trading market officially launched on July 21, 2021, initially incorporating 2,225 power generation companies and covering over 4 billion tons of CO2 emissions, thus becoming the largest carbon market globally in terms of greenhouse gas emission coverage. This study selects the daily closing prices of carbon emission rights trading from July 16, 2021, to February 21, 2024, as the second variable, with data sourced from the national carbon trading platform.

4.1.3 Data Processing

To ensure consistency in the units of variables, the original data were processed as follows: Unit conversion: The coking coal futures contracts on the Dalian Commodity Exchange are traded in units of 60 tons per contract. Therefore, the collected original data were divided by 60 to convert the prices to yuan per ton. Logarithmic transformation: To enhance the accuracy of the study and eliminate the heteroscedasticity of the price time series, the selected data were subjected to logarithmic transformation. The processed variable names are the daily closing prices of the main coking coal continuous contracts over the past six years (LNJM9999A), the daily closing prices of the main coking coal continuous contracts over the past three years (LNJM9999B), and the daily closing prices of carbon emission rights over the past three years (LNTPFQ).

Table 1. Data Sources and Descriptions

Variable Category	Variable Name	Variable Symbol	Data Source	Unit
Coking Coal Futures Prices	Daily Closing Prices of Main Continuous Futures Contracts (Past 6 Years)	LNJM9999A	Tonghuashun Futures Trading Platform	yuan/ton
	Daily Closing Prices of Main Continuous Futures Contracts (Past 3 Years)	LNJM9999B	Tonghuashun Futures Trading Platform	yuan/ton
Carbon Trading Prices	Daily Closing Prices of Carbon Emission Allowances (Past 3 Years)	LNTPFQ	National Carbon Trading Platform	yuan/ton

4.2 Descriptive Analysis of Data

4.2.1 Descriptive Analysis of Coking Coal Futures Contracts

Figure 1 shows the price trend of the main continuous coking coal futures contracts from January 1, 2018, to February 21, 2024.

Figure 1. Price Trend of Main Continuous Coking Coal Futures Contracts

As shown in Figure 1, the random fluctuation trend of China's main continuous coking coal futures contracts is quite noticeable. From January 1, 2018, to January 1, 2020, prices were relatively low and stable, with the lowest price at 1,035.5 yuan per contract (each contract representing 60 tons). From January 1, 2020, to January 1, 2022, coking coal futures prices rapidly increased to a peak of 3,847 yuan per contract, followed by a significant drop. Shortly after, prices began to rise again. Overall, the price trend of coking coal futures contracts within this period shows a fluctuating upward trajectory.

Table 2. Descriptive Statistics of Main Continuous Coking Coal Futures Contract Closing Prices

Obs	Sum of wgt.	Mean	Std. dev.	Variance	Skewness	Kurtosis
1,488	1,488	1657.996	505.6052	255636.6	1.270442	4.211379

The descriptive analysis of coking coal futures contract prices (see Table 2) reveals that over the past six years, the mean of the main continuous coking coal futures contract closing prices is 1657.996. The kurtosis is 4.211379, higher than the normal distribution value of 3, and the skewness is 1.270442, which is notably different from 0. This indicates that the time series of coking coal futures prices has the characteristics of leptokurtosis and heavy tails.

4.2.2 Comparative Analysis of Carbon Emission Rights and Coking Coal Futures Contracts

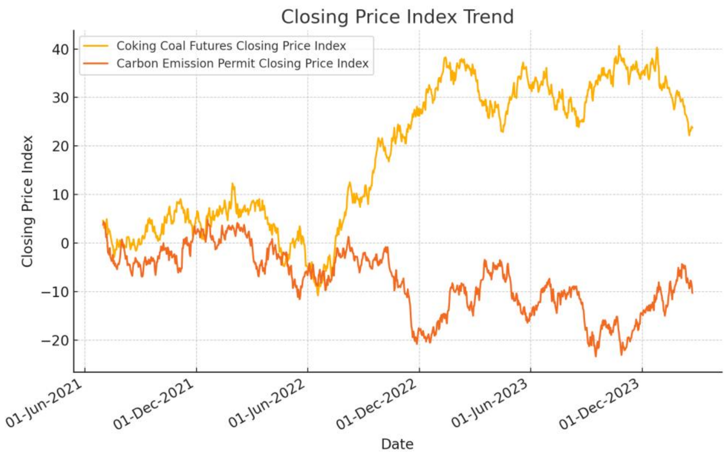

Figure 2. Trend Comparison of Logged Coking Coal Futures and Carbon Emission Rights since 2021

By comparing the logged daily closing prices of coking coal futures and carbon emission rights per ton over the past three years (see Figure 2), Figure 2 presents the trend comparison of the two. Overall, the price of carbon emission rights exhibits a fluctuating upward trend, while the trend of coking coal futures shows a fluctuating downward trend. From June 2021 to January 2022, the price trend of carbon emission rights declined, likely due to the carbon trading market's recent launch, initially involving only power generation companies and not being open to all market participants. Compared to the mature coking coal futures market, the limited participation in carbon trading restricted its financial attributes. At that time, the market supply-demand relationship had not yet formed a stable balance, and China's carbon trading market was in its nascent stage, with participating companies learning through experience. Therefore, the prices did not accurately reflect the true carbon trading market. Over time, as market participants grew and the market adjusted, the overall trend of carbon emission rights prices showed a fluctuating upward trajectory. In contrast, coking coal futures exhibited larger price fluctuations, but their overall trend was opposite to that of carbon trading. As the price of carbon emission rights gradually increased, the price trend of coking coal futures contracts showed a fluctuating downward trend. The comparison chart suggests a certain correlation between the two. Based on data availability, the following empirical section selects the closing prices of the two variables over the past three years (629 trading days) as the sample for analysis.

5. Empirical Testing

5.1 ADF Test

To eliminate spurious regression caused by the non-stationarity of variable data and to obtain stationary time series, this study first performs a unit root test on the variables. The stationarity tests for the two variables, LNJM9999B and LNTPFQ, are conducted, with results shown below. The ADF test results for the first-order differences of the variables are presented in Table 3, and the ADF test results for the first-order differences of the variables are shown in Table 4.

Table 3. ADF Test Results of Original Variables under Various Models

Variable	Test Form (c,t,n)	ADF Value	1% Critical Value	5% Critical Value	10% Critical Value	Conclusion
LNJM9999B	(0,0,1)	-2.518	-3.451	-2.875	-2.57	Non-stationary
	(1,0,1)	-1.97	-2.342	-1.651	-1.285	Non-stationary
	(1,1,1)	-2.786	-3.985	-3.425	-3.13	Non-stationary
LNTPFQ	(0,0,1)	0.145	-3.451	-2.875	-2.57	Non-stationary
	(1,0,1)	0.145	-2.337	-1.649	-1.284	Non-stationary
	(1,1,1)	-1.679	-3.985	-3.425	-3.13	Non-stationary

Note: c=1 indicates the presence of a constant term, c=0 indicates the absence of a constant term; t=1 indicates the presence of a trend term, t=0 indicates the absence of a trend term; p indicates the lag order.

Table 4. ADF Test Results of First-Order Differenced Variables under Various Models

Variable	Test Form (c,t,n)	ADF Value	1% Critical Value	5% Critical Value	10% Critical Value	Conclusion
LNJM9999B	(0,0,0)	-21.385	-3.451	-2.875	-2.57	Stationary
	(1,0,0)	-21.385	-2.337	-1.649	-1.284	Stationary
	(1,1,0)	-21.371	-3.985	-3.425	-3.13	Stationary
LNTPFQ	(0,0,0)	-17.991	-3.451	-2.875	-2.57	Stationary
	(1,0,0)	-17.991	-2.337	-1.649	-1.284	Stationary
	(1,1,0)	-18.058	-3.985	-3.425	-3.13	Stationary

Note: c=1 indicates the presence of a constant term, c=0 indicates the absence of a constant term; t=1 indicates the presence of a trend term, t=0 indicates the absence of a trend term; p indicates the lag order.

The test results demonstrate that the original variable sequences are non-stationary at the 1%, 5%, and 10% significance levels. However, the data sequences after first-order differencing are stationary. Thus, the subsequent empirical research in this paper will employ the first-order differenced data sequences for investigation.

5.2 Johansen Cointegration Test

The unit root test results show that LNJM9999B and LNTPFQ are integrated of order one, allowing for further cointegration testing. Using the Engle-Granger two-step method, the residual sequence was obtained and subjected to a unit root test (see Table 5). As indicated in the table, the residual sequence rejects the null hypothesis at the 5% significance level, demonstrating a cointegration relationship between coking coal futures and carbon emission rights. This indicates a long-term equilibrium relationship between the two, even though short-term fluctuations may occur. The subsequent empirical research will focus on constructing a VAR vector model and will not address the selection of cointegration vectors. Therefore, this paper only establishes the cointegration relationship between the two variables without further deriving the specific cointegration vectors.

Table 5. Johansen Cointegration Test and Unit Root Test of Residual Sequence

		Dickey –Fuller		
	Test	———critical value ———		
	statistic	0.01	0.05	0.1
Z(t)	-10.804	-3.464	-2.881	-2.571

MacKinnon approximate p-value for Z(t) = 0.0000.

5.3 VAR Model Construction and Granger Causality Test

5.3.1 Lag Order Selection

A critical step before constructing the VAR model is determining the lag order ppp. Choosing a lag order that is too long results in too few degrees of freedom and larger parameter errors, while a lag order that is too short may not adequately capture the relationships between variables. The information criterion is used to determine the order of the VAR system (see Table 6). The stars in the table represent the optimal results under different criteria, with BIC indicating the optimal lag order as one and AIC indicating the optimal lag order as two. To be prudent, this paper selects a lag order of 2, thus constructing a second-order lagged vector autoregression model (see Table 7), where most coefficients are significantly positive.

Table 6. Optimal Lag Order Parameter Table

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2757.46				5.00E-07	-8.83161	-8.82609	-8.81739
1	2772.08	29.229*	4	0	4.80E-07	-8.86563	-8.84906*	-8.82298*
2	2776.46	8.7738	4	0.067	4.8e-07*	-8.86687*	-8.83925	-8.79578
3	2778.14	3.3497	4	0.501	4.90E-07	-8.85942	-8.82075	-8.75989
4	2779.69	3.1104	4	0.54	4.90E-07	-8.85159	-8.80186	-8.72362

Table 7. VAR(2) Model Estimation Results

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dlntpfq						
L1.	-0.1815327	0.0398073	-4.56	0	-0.2595535	-0.1035118
L2.	-0.0692184	0.0393465	-1.76	0.079	-0.1463361	0.0078993
djm9999b						
L1.	-0.0079757	0.0197023	-0.4	0.686	-0.0465915	0.0306401
L2.	0.0118177	0.0196931	0.6	0.548	-0.0267801	0.0504154
_cons	0.0007946	0.0007358	1.08	0.280	-0.0006476	0.0022368
dlntpfq						
L1.	-0.0508987	0.0806479	-0.63	0.528	-0.2089658	0.1071683
L2.	0.1044033	0.0797144	1.31	0.190	-0.0518339	0.2606406
djm9999b						
L1.	-0.1245119	0.039916	-3.12	0.002	-0.2027459	-0.0462779
L2.	-0.0617534	0.0398974	-1.55	0.122	-0.1399509	0.0164441
_cons	-0.0003778	0.0014907	-0.25	0.800	-0.0032996	0.002544

5.3.2 Residual Test and Stability Test

Based on the constructed VAR(2) model, we further test whether the residuals are white noise. The test results (see Table 8) indicate that the null hypothesis of "no autocorrelation" in the residuals can be accepted.

Table 8. Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	2.6325	4	0.62107
2	2.6944	4	0.6102

Subsequently, the stability of the VAR(2) model system was further tested. The test results (see Figure 3) show that all the reciprocal roots of the characteristic polynomial of the VAR(2) model are less than 1, and all the points lie within the unit circle. This indicates that the constructed vector autoregression model system has passed the stability test, validating the conclusions drawn from the VAR(2) model estimation results.

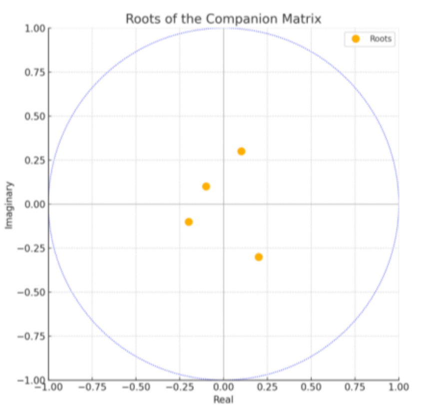

Figure 3. Stability Test Diagram of VAR Results

5.3.3 Granger Causality Test

If, given the past information of both carbon emission rights prices and coking coal futures prices, the prediction of carbon emission rights prices is better than that based solely on their own past information, it suggests that coking coal futures prices help explain the future changes in carbon emission rights prices. This means that coking coal futures prices are the Granger cause of carbon emission rights prices. Granger causality testing is essentially a statistical method for predicting stationary time series data and is only suitable for forecasting variables in econometrics. It cannot be used as definitive proof of true causality. The test results (see Table 9) indicate that carbon emission rights prices are not the Granger cause of coking coal futures prices, and conversely, coking coal futures prices are also not the Granger cause of carbon emission rights prices.

Table 9. Granger Causality Test Results

Equation	Excluded	chi2	df	Prob > chi2
dlntpfq	dlnjm9999b	0.59018	2	0.744
dlntpfq	ALL	0.59018	2	0.744
dlnjm9999b	dlntpfq	2.45	2	0.294
dlnjm9999b	ALL	2.45	2	0.294

5.4 Impulse Response and Variance Decomposition

5.4.1 Impulse Response Analysis

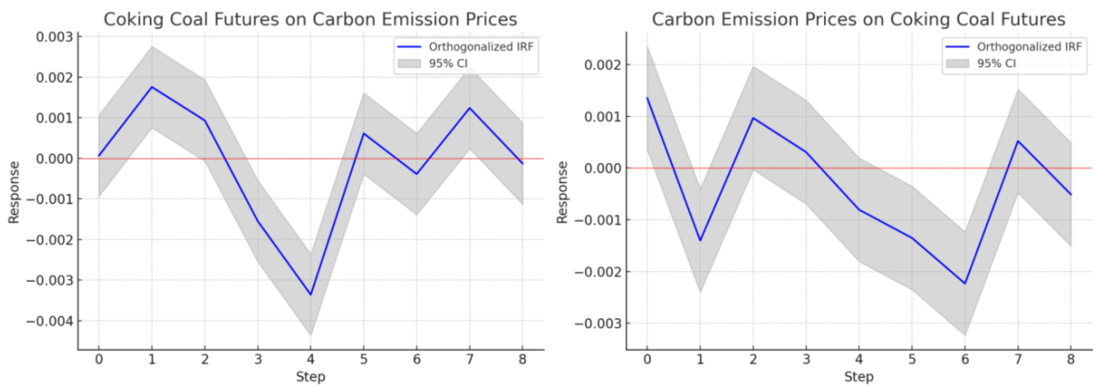

Figure 4. Impulse Response Function Graph

To further analyze the dynamic relationships between variables, this paper utilizes the impulse response function of the VAR(2) model. The impulse response function represents the effect of a one standard deviation positive shock to a variable on itself and other variables in the system both in the current and future periods. The impulse response results (see Figure 4) show that a one standard deviation positive shock to the carbon emission rights price initially has a negative impact on the coking coal futures price in the first period. This impact then rises sharply and turns positive in the second period, reaching a peak before declining again and turning negative in the third period. The impact gradually returns to zero in subsequent periods, indicating that a one standard deviation shock to the carbon emission rights price affects the coking coal futures price for about six periods. The maximum positive impact exceeds 0.002, while the negative impact is weaker, less than 0.001. The right-hand graph shows the impact of a one standard deviation shock to the coking coal futures price on the carbon emission rights price. Although it fluctuates, the impact is much weaker compared to the left-hand impulse response. This suggests that the impact of the carbon emission rights price on the coking coal futures price is much greater than the impact of the coking coal futures price on the carbon emission rights price.

5.4.2 Variance Decomposition

To quantitatively and intuitively depict the relationships between variables, this paper further utilizes variance decomposition to analyze the contribution of each variable in the VAR(2) model. The results are shown in Table 10.

Table 10. Variance Decomposition of Variables in VAR(2) Model - Table A

	(1)	(1)	(1)	(2)	(2)	(2)
Step	fevd	Lower	Upper	fevd	Lower	Upper
0	0	0	0	0	0	0
1	1	1	1	1.50E-06	-0.000193	0.000196
2	0.999747	0.997301	1.00219	0.00063	-0.003309	0.004569
3	0.998942	0.993524	1.00436	0.004053	-0.00614	0.014246
4	0.998903	0.993303	1.0045	0.00425	-0.006393	0.014894
5	0.998899	0.993276	1.00452	0.004267	-0.006417	0.014952
6	0.998898	0.99327	1.00452	0.004272	-0.006423	0.014968
7	0.998898	0.99327	1.00452	0.004272	-0.006423	0.014968
8	0.998898	0.99327	1.00452	0.004272	-0.006423	0.014968

Table 10. Variance Decomposition of Variables in VAR(2) Model - Table B

	(3)	(3)	(3)	(4)	(4)	(4)
Step	fevd	Lower	Upper	fevd	Lower	Upper
0	0	0	0	0	0	0
1	0	0	0	0.999998	0.999804	1.00019
2	0.000253	-0.002194	0.002699	0.99937	0.995431	1.00331
3	0.001058	-0.00436	0.006476	0.995947	0.985754	1.00614
4	0.001097	-0.004503	0.006697	0.99575	0.985106	1.00639
5	0.001101	-0.004521	0.006724	0.995733	0.985048	1.00642
6	0.001102	-0.004525	0.00673	0.995728	0.985032	1.00642
7	0.001102	-0.004525	0.00673	0.995728	0.985032	1.00642
8	0.001102	-0.004525	0.00673	0.995728	0.985032	1.00642

The results in Table 10-a show the following: (1) The contribution of the carbon emission rights price to its own price change is 99.88%. (2) The contribution of the carbon emission rights price to the coking coal futures price change is 0.42%. The results in Table 10-b show the following: (3) The contribution of the coking coal futures price change to the carbon emission rights price change is 0.11%. (4) The contribution of the coking coal futures price to its own price change is 98.57%. Overall, the contribution of the carbon emission rights price to the coking coal futures price is nearly four times that of the coking coal futures price to the carbon emission rights price.

6. Research Conclusions and Policy Recommendations

6.1 Research Conclusions

From the empirical analysis of coking coal futures prices and carbon emission rights prices, the following conclusions are drawn:

6.1.1 Based on Price Trend Analysis

Over the past six years, the coking coal futures price has shown an overall upward trend with fluctuations, particularly after the announcement of China's "dual carbon" goals in 2020, which significantly increased price volatility. This indicates the strong influence of the "dual carbon" policy on the coking coal futures market. The policy's introduction has heightened market uncertainty, prompting enterprises to make significant adjustments to their expectations of future carbon quotas and production costs in the short term, leading to greater price volatility. Notably, as a key component of the steel industry chain, the price fluctuations of coking coal impact not only coke production but also downstream industries such as steel, thereby causing a ripple effect throughout the entire economic system.

6.1.2 Based on Cointegration Analysis

The Johansen cointegration test indicates a long-term cointegration relationship between coking coal futures prices and carbon emission rights prices. This suggests that while short-term fluctuations and deviations may occur, there is a dynamic equilibrium relationship between the two in the long term. This relationship shows that market mechanisms adjust the two variables to a common equilibrium state over time through price signals. The cointegration relationship between coking coal futures prices and carbon emission rights prices also reflects the market's joint response and adaptation mechanism to coking coal and carbon emissions under the "dual carbon" goals, which is of considerable significance for policymakers.

6.1.3 Based on Granger Causality Test

The Granger causality test results demonstrate that the carbon emission rights price is not the Granger cause of the coking coal futures price, and vice versa. This indicates that, within the current data sample and research methods, there is no significant unidirectional predictive relationship between the two. Specifically, even when considering historical data, changes in the carbon emission rights price do not significantly predict changes in the coking coal futures price, and vice versa. This conclusion suggests that while there is a long-term cointegration relationship, the short-term fluctuations and causal mechanisms are more complex, likely influenced by other external factors such as macroeconomic policies, market sentiment, and global energy prices.

6.1.4 Based on Impulse Response and Variance Decomposition

The impulse response function and variance decomposition analysis reveal that the carbon emission rights price has a stronger impact on the coking coal futures price, while the coking coal futures price has a weaker impact on the carbon emission rights price. This indicates that in the interaction between the carbon market and the coking coal market, fluctuations in the carbon emission rights price significantly guide the coking coal futures price. Specifically, when the carbon emission rights price changes, the coking coal futures price reacts strongly, reflecting the transmission effect of the carbon market on the energy market and its policy influence. Conversely, the fluctuations in the coking coal futures price have a relatively smaller impact on the carbon emission rights price, suggesting that changes in the coking coal market are more influenced by factors outside the carbon market.

6.2 Policy Recommendations

6.2.1 Strengthen Supervision of the Coking Coal Futures Market

To address the impact of the "dual carbon" policy on coking coal futures prices, the government should strengthen market supervision and employ macroeconomic policies to stabilize the market and prevent extreme price fluctuations. Specific measures include adjusting interest rates and reserve requirements to control market liquidity and stabilize the coking coal futures market; providing subsidies and tax incentives to support relevant enterprises in coping with market fluctuations and ensuring supply chain stability; and establishing market monitoring mechanisms to track the dynamics of the coking coal futures market in real-time, enabling timely intervention. For example, during severe market fluctuations, appropriately increasing the reserve requirement can reduce market liquidity and curb speculative behavior. The government can subsidize coking coal-related enterprises through special funds to lower their operating costs and alleviate market pressure. Additionally, utilizing big data and artificial intelligence technologies to monitor market trading data and price trends can help provide early warnings of potential market anomalies. Through these comprehensive measures, the government can effectively respond to market fluctuations caused by policy changes, ensuring the stable operation of the coking coal futures market.

6.2.2 Optimize the Carbon Market Structure

China's current carbon market coverage is relatively narrow and needs to be gradually expanded to include more participants, thereby increasing market activity and optimizing the market structure. Specific measures include gradually incorporating high-emission industries such as steel, cement, and chemicals into the carbon trading market to increase market capacity, enhance trading volume, and promote broader participation in carbon reduction efforts; attracting more financial institutions, enterprises, and investors to the carbon market by providing policy guidance and market incentives, encouraging banks, insurance companies, and investment funds to join the carbon market to boost capital supply; and strengthening training for enterprises and investors through workshops, seminars, and simulated trading activities to improve their understanding and operational capabilities in the carbon market. These measures will diversify the participants, improve the market structure, significantly enhance market activity, and ensure the healthy development of the carbon market.

6.2.3 Improve Carbon Quota Management

Carbon quota policies need dynamic adjustment to balance market supply and demand, prevent price fluctuations from impacting manufacturing, and ensure emission reduction targets are met alongside economic development. Specific measures include periodically adjusting carbon quotas based on market supply and demand conditions and emission reduction goals to maintain smooth market operation; establishing a carbon market regulation fund to intervene during market fluctuations and stabilize carbon prices; and increasing the transparency of carbon quota allocation and usage by establishing a robust information disclosure system to enhance market confidence. For example, flexibly adjusting quota allocations according to different seasons and industry characteristics can avoid seasonal supply-demand imbalances. The government can establish special funds to buy or sell carbon quotas during severe market fluctuations to stabilize prices. Regularly publishing market reports and quota usage details ensures that market participants receive timely information, enabling them to make informed future market predictions. These measures will make carbon quota management more scientific and rational, effectively mitigating the risks associated with market fluctuations and ensuring the smooth achievement of emission reduction targets.

6.2.4 Promote Innovation in Carbon Financial Products

Drawing from the experience of mature international markets, developing diversified carbon financial products can enhance market operation efficiency and attractiveness. Specific measures include designing financial products such as carbon forwards and carbon options based on domestic market demand to diversify transaction types, introducing varied financial tools to offer more choices for market participants, thereby increasing liquidity and risk management capabilities; promoting and training market participants to improve their recognition and acceptance of new financial products, expanding market size; and the government should provide policy support to promote the development and application of carbon financial products, fostering market innovation. For example, formulating preferential policies to encourage financial institutions and enterprises to develop and use carbon financial products can enhance overall market efficiency. These measures will significantly boost market operation efficiency and attractiveness through the innovation of carbon financial products, supporting the achievement of the "dual carbon" goals.

7. Conclusion

This study primarily found that coking coal futures prices have shown an upward trend with fluctuations over the past six years, especially with increased volatility after the "dual carbon" goals were proposed. There is a long-term cointegration relationship between coking coal futures prices and carbon emission rights prices, but no significant unidirectional predictive relationship. The impact of carbon emission rights prices on coking coal futures prices is stronger than vice versa. The research contributes by revealing the dynamic relationship between coking coal futures and carbon emission rights prices under the "dual carbon" background, providing a new perspective for policy formulation. This paper suggests strengthening the supervision of the coking coal futures market, optimizing the carbon market structure, improving carbon quota management, and promoting innovation in carbon financial products to foster healthy market development.

The contribution of this study lies in uncovering the dynamic relationship between coking coal futures prices and carbon emission rights prices, offering a new perspective for understanding the linkage mechanisms between the energy market and the carbon market under the "dual carbon" goals. The policy and practical recommendations of this paper include strengthening the supervision of the coking coal futures market, optimizing the carbon market structure, improving carbon quota management, and promoting innovation in carbon financial products. These recommendations aim to promote the healthy development of China's carbon market and coking coal market.

However, this study also has some limitations. First, the data selection range is relatively short, covering only the recent trends of coking coal futures and carbon emission rights prices. Future research could extend the data range to capture more market changes. Second, this paper mainly uses the VAR model for analysis. Future research could try more diverse methods, such as the GARCH model, to verify the robustness of the results. Additionally, this study did not consider the impact of macroeconomic factors on coking coal futures and carbon emission rights prices. Future research could incorporate macroeconomic variables into the model to fully understand their impact mechanisms. Future research directions could be expanded in the following areas: first, further expanding the data range and sample size to verify the generality of the conclusions; second, trying more diverse econometric methods to enhance the robustness of the research results; third, considering the impact of macroeconomic variables to comprehensively understand the dynamic relationship between coking coal futures and carbon emission rights prices; and fourth, exploring the impact of different policy measures on market linkage effects to propose more targeted policy recommendations.

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Author Contributions

Associate Professor Li Min and his master's student Gu Shiguang were responsible for the study design and revision of the article. Sandy, a master's student, was responsible for data collection. Gu Shiguang drafted the initial manuscript, and Associate Professor Li Min revised it. All authors read and revised the final manuscript. There are no special agreements regarding authorship; this article was written by Gu Shiguang under the guidance of his supervisor, Associate Professor Li Min, with Sandy assisting in data collection. All listed authors have made equal contributions to this study.

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Competing interests

Gu Shiguang, Li Min, and Sandy declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Informed consent

Obtained.

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The Publication Ethics Committee of the Canadian Center of Science and Education.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

References

Bentzen, J. (2007). Does OPEC influence crude oil prices? Testing for co-movements and causality between regional crude oil prices. *Applied Economics*, *39*(11), 1375-1385. https://doi.org/10.1080/00036840600606344

Liu, J. Y, Yang, F. J., & Li, Y. B. (2020). A study on long-term factors affecting the price volatility of China's carbon emissions trading—based on carbon prices at the Beijing Environment Exchange. *Statistics Theory and Practice*, *3*, 11-16.

Ma, C. Q., She, S. X., Chen, Y. L., et al. (2009). A study on information spillover in the Shanghai fuel oil futures market in China. *Journal of Management Science*, *12*(3), 92-101.

Wei, W. X, & Bo, Q. (2007). The volatility of domestic and international oil prices and their interactive relationship. *Economic Research*, *(12)*, 130-141.

Wei, Y., Zhang, J. H., & Chen, X. D. (2022). Forecasting methods for China's carbon emissions trading prices based on DMS and DMA: Empirical evidence from the Hubei carbon market. *Systems Engineering*, *40*(4), 1-16.

Xue, Y., & Huang, (2017). Study on the price co-movement among the Asia Pacific, European and Chinese coal markets–based on the empirical analysis of MS-VEC model. *Applied Economics*, *49*(7). https://doi.org/10.1080/00036846.2016.1205720

Yan, Z. M., Yang, Z. M., & Du, K. R. (2017). Measurement of low-carbon technology innovation and its impact on carbon intensity. *Finance & Trade Economics*, *38*(08), 112-128.

Yang, S., He, L. Y., Zhou, S. D., et al. (2008). Cointegration analysis of DCE soybean and soybean meal futures contract prices. *China Management Science*, *16*(Suppl. 1), 302-305.

Yang, W. P., & Yuan, X. L. (2008). Analysis of the impact of foreign trade and FDI on environmental pollution: An impulse response function analysis based on China's time series (1982–2006). *World Economy Research*, *12*, 62-68, 86.

Yi, L., Yang, L., Li, Z. P., et al. (2017). A study on the influencing factors of EU carbon prices and their implications for China. *China Population, Resources and Environment*, *27*(6), 42-48.

Zhao, L. D, Fan, C., & Wang, H. X. (2021). Time-varying spillover effects between China's carbon market and energy market: An empirical study based on the spillover index model. *Journal of Beijing Institute of Technology (Social Sciences Edition)*, *23*(1), 28-40.