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Analysis of Factors Influencing the Price of Beijing Carbon Emission Allowance Based on the VAR Model

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Abstract

Effectively constructing a carbon emission trading Market is crucial for China to achieve its goals of carbon peaking and carbon neutrality. However, carbon emission allowance prices are influenced by various factors. This paper employs a Vector Autoregression (VAR) model, using the average transaction price of Beijing Carbon Emission Allowances (BEA) as the research subject. It analyzes related indicators from four aspects: energy prices, macroeconomic conditions, environmental factors, and public sentiment. The results show that among energy price factors, coal and oil prices have a positive impact on BEA prices, while natural gas has a negative impact. Macroeconomic factors initially have a negative impact, followed by fluctuating recovery. Environmental factors, such as the Air Quality Index (AQI) and maximum temperature, initially have a positive impact on BEA prices, followed by fluctuating recovery, while the minimum temperature has the opposite effect. Public sentiment has a significant negative impact on BEA price fluctuations. The empirical results of this study can help investors better understand the changes in the prices of carbon emission allowance, provide references for policymakers, and offer foundations for constructing a national carbon emission trading market that reflects comprehensive and accurate information.

Keywords: Carbon Emission Allowance, Beijing, Public Sentiment, VAR Model, Impulse Response Analysis

1. Introduction

As global climate issues become increasingly prominent and the greenhouse effect intensifies, carbon reduction has become an urgent task. Establishing a effective carbon emission trading market to constrain and limit carbon dioxide emissions and forming an efficient and responsive carbon trading price mechanism are crucial. China has undertaken a series of initiatives in this regard. In 2011, the National Development and Reform Commission issued the "Notice on Launching Pilot Carbon Emission Trading Programs," designating seven regions—Shenzhen, Beijing, Shanghai, Tianjin, Chongqing, Hubei, and Guangdong—as pilot carbon trading zones. In January 2016, the "Notice on Key Tasks for Launching the National Carbon Emission Trading Market" was issued, setting the goal of launching the national carbon emission trading market in 2017. Finally, on July 16, 2021, the national carbon emission trading market officially opened, aiming to achieve "carbon peak" by 2030 and "carbon neutrality" by 2060.

As China's political and cultural center and one of the most economically developed cities, Beijing holds significant strategic importance as a pilot city for the national carbon emission trading market. Therefore, this paper focuses on the trading price of BEA in Beijing, exploring the factors influencing its price, analyzing the underlying constraints, and proposing relevant recommendations to support China's goals of carbon peaking and carbon neutrality and provide insights for the establishment of the national carbon emission trading market, thereby mitigating potential risks.

2. Literature Review

Price, as a primary research subject in economics, inherently carries high uncertainty and is influenced by various factors. Carbon emission allowance prices, as an emerging price category, are no exception. Qiao et al. (2024) found that key factors influencing carbon emission trading prices include WTI crude oil prices, carbon emission futures (ICE), and the CSI 300 Index. Shen and Luo, (2022) used the LSTM algorithm to study the impact of energy prices, climate, international carbon markets, and industrial development levels on carbon emission allowance prices. Deng et al. (2025) also emphasized the significant impact of energy prices on carbon emission allowance prices and used them as a key factor in predicting carbon emission allowance prices. Additionally, energy-intensive industries have a strong overall correlation with carbon emission markets, especially in the long term (Xu & Lien, 2025). Zhou et al. Zhou et al. (2025) argued that economic uncertainty and climate factors also significantly impact carbon prices, though these are often overlooked. Wang et al. (2025) selected energy, economic, environmental, and public attention variables as predictors for carbon emission prices. Sun et al. (2024) also highlighted the importance of international carbon emission allowance prices, macroeconomic environment changes, energy prices, and public attention to climate change on carbon emission prices, along with historical carbon price and Baidu Search Index keywords (Jiang, Che, Li, Hu, & Xu, 2025).

Various models have been used to study the factors influencing carbon emission prices. Xiong Pingping et al. Xiong and Wang (2024) used the VAR model to examine the transmission path between coal prices and carbon emission trading prices, as well as the causal relationships between energy consumption structure, energy efficiency, and dynamic correlation coefficients. Zhou & Li, (2019) employed a Vector Autoregression-Vector Error Correction (VAR-VEC) model to study the dynamic relationships between energy prices, macroeconomic indicators, air quality, and carbon emission trading prices, finding that carbon trading prices are significantly influenced by macroeconomic indicators. Other models include ARMA-GARCH and fixed-effects models with variable intercepts (Bai Qiang, Dong Jie, & Tian Yuanchun, 2022), as well as VAR-MVGARCH-DCC models (Cai Tongjuan, Lin Runhong, & Zhang Xu, 2023).

In summary, the existing literature provides novel theoretical support for research on carbon emission allowance trading. However, there is still a lack of sufficient exploration into the volatility characteristics of carbon emission allowance prices and their underlying influencing factors, with significant discrepancies in the conclusions drawn. Therefore, this paper focuses specifically on the Beijing carbon emission market, using the VAR model to introduce usually overlooked but crucial factors such as public sentiment and climate. It explores the factors influencing carbon emission allowance price fluctuations from four dimensions: energy prices, macroeconomic conditions, environmental factors, and public sentiment, aiming to provide useful references for the stable operation of China's carbon emission trading market.

3. Methodology and Data

3.1 VAR Model

The VAR model is based on statistical data, analyzing the dynamic behavior of each variable and its lagged values to depict the evolution trajectory of the model system and assess the specific impact of exogenous impulses on each variable (Xiong Pingping & Wang Yaqi, 2024). The VAR model can simultaneously consider multiple variables and their lagged effects on the research subject, making it particularly adept at capturing dynamic relationships between variables, especially time-lagged effects.

In the carbon emission allowance market, prices are often influenced by lots of lagged impacts, such as historical prices, energy prices, macroeconomic conditions, and so on. The Vector Autoregression Model (VAR) model can accurately capture these dynamic relationships. Therefore, following the approach of Xiong Pingping et al., this paper processes data by using Excel and constructs a VAR model by using Stata 15.0 to explore the factors influencing BEA prices and their relationships. The mathematical expression of the model is shown in Equation (1).

$$y_n = \partial_1 y_{n-1} + \cdots + \partial_p y_{n-p} + \mathcal{E}_t \qquad t = 1,2,3,\cdot\cdot, T \tag{1}$$

Where n is the sample size, yn is a k-dimensional matrix, ∂_2, …, ∂_p are k×k coefficient matrices to be estimated, p is the lag order of the VAR model, which needs to be determined based on information criteria, and ε_n is a k-dimensional random disturbance term.

Given the numerous parameters in the VAR model and the difficulty in interpreting their economic significance, this paper focuses on the impulse response function. The mathematical expression is shown in Equation (2).

$$IRF_{ji}(h) = \frac{\partial y_{j,t+p}}{\partial \varepsilon_{i,t}} \tag{2}$$

Where IRFji(h) represents the impact of the j variable on the i variable, h represents the lag period, and Equation (2) shows the impact of a unit impulse to the j variable yj at time t on the i variable over the h periods.

3.2 Data Sources

Based on the transaction data of Beijing Carbon Emission Allowances (BEA) published by the China Beijing Green Exchange, the daily average price is used as the dependent variable, represented by BEA.

Given the numerous factors influencing BEA prices, this paper analyzes them from four aspects: energy prices, macroeconomic conditions, environmental factors, and public sentiment. Energy consumption is a major source of carbon dioxide emissions, primarily from coal, oil, and natural gas. This paper selects the closing price of the coke index, international crude oil spot price, and liquefied natural gas futures closing price as energy price data, denoted as Coal, Oil, and Gas, respectively. Data sources include the Dalian Commodity Exchange, iFinD, and the New York Mercantile Exchange (NYMEX), with oil and natural gas prices converted to RMB using the spot exchange rate. For macroeconomic conditions, the CSI 300 Index is selected to reflect domestic macroeconomic conditions, with data sourced from the Shanghai Stock Exchange, denoted as CSI300. Since exchange rates affect commodity prices and may impact carbon prices, the USD/CNY spot exchange rate is selected to reflect international market changes, with data sourced from the China Foreign Exchange Trade System, denoted as ER. For environmental factors, the Beijing Air Quality Index (AQI) is selected to reflect air quality, with data sourced from the China Air Quality Online Monitoring and Analysis Platform, denoted as AQI. The daily minimum and maximum temperatures in Beijing are selected to represent extreme weather changes, with data sourced from the National Meteorological Center of CMA, denoted as Tmin and Tmax. Public sentiment is represented by the combined search volume of "carbon trading" on Baidu's PC and mobile platforms, with data sourced from Baidu, denoted as BDI.

The sample period for the data is from December 2013 to April 2024, excluding non-trading days. Missing data are filled using a moving average window method, and all data are daily. Variable classifications and data sources are shown in Table 1.

Table 1. Variable Classification and Data Sources

first-level indicator	second-level indicator	Data Source	Symbol
Historical Carbon Price	Beijing Carbon Emission Allowance: Average Transaction Price	China Beijing Green Exchange	BEA
Energy Prices	Coke Index: Closing Price	Dalian Commodity Exchange	Coal
	International Crude Oil Spot Price	iFinD	Oil
	LNG Futures: Closing Price	New York Mercantile Exchange (NYMEX)	Gas
Macroeconomic Conditions	CSI 300 Index	Shanghai Stock Exchange	CSI300
	Spot Exchange Rate: USD/CNY	China Foreign Exchange Trade System	ER
Environmental Factors	Beijing Air Quality Index	China Air Quality Online Monitoring and Analysis Platform	AQI
	Daily Minimum Temperature	China Meteorological Administration	Tmin
	Daily Maximum Temperature	China Meteorological Administration	Tmax
Public Sentiment	Baidu Index: Carbon Trading	Baidu	BDI

4. Empirical Research

4.1 Descriptive Statistics

The dataset of BEA contains 1,125 entries, excluding non-trading days. Other indicators are retained based on BEA trading dates. BEA prices fluctuate between 24 and 149.6 RMB/ton, showing significant volatility. Table 2 presents the descriptive statistics of the original data.

Table 2. Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
BEA	1,125	71.64	25.55	24	149.6
Coal	1,125	2,086	653.5	619	4,281
Oil	1,125	422.2	133.0	90.99	789.1
Gas	1,125	22.37	10.68	10.66	66.56
CSI300	1,125	3,896	619.9	2,877	5,626
ER	1,125	6.777	0.250	6.280	7.260
Tmin	1,125	10.87	11.09	-13.70	28.70
Tmax	1,125	21.32	11.18	-6	40.40
AQI	1,125	90.07	55.21	0	500
BDI	1,125	551.9	758.9	137	15,750

4.2 White Test

To construct the VAR model, the presence of heteroskedasticity must be ruled out first. The White test is a common method for this purpose. This paper conducts the White test, and the results are shown in Table 3. At the 1% confidence level, the hypothesis of homoskedasticity is rejected, indicating the presence of heteroskedasticity. Therefore, all indicator data are logarithmically transformed, prefixed with "ln_", such as ln_BEA, ln_Coal, etc.

Table 3. White Test

White's test for Ho: homoskedasticity			
against Ha: unrestricted heteroskedasticity			
chi2(54) = 270.9			
Prob>chi2 = 0.0000			
Cameron & Trivedi's decomposition of IM-test			
Source	chi2	df	p
Heteroskedasticity	270.9	54	0
Skewness	49.60	9	0
Kurtosis	9.040	1	0.00260
Total	329.5	64	0

4.3 ADF Test and Cointegration Test

Since only stationary data (i.e., data without unit roots) can be used to build a VAR model, this paper conducts the ADF test. The results show that ln_BEA, ln_Coal, ln_Oil, ln_Gas, ln_CSI300, ln_ER, and ln_BDI are non-stationary series. Therefore, all data are first-order differenced and prefixed with "D.", such as D.ln_BEA, D.ln_Coal, etc.. Then this paper conduct stability analysis. Finally, all first-order differenced data are stationary, that is to say they are first-order integrated series. Subsequently, the Johansen cointegration test is conducted to examine whether there is a long-term stable relationship between the data series. The results indicate that D.ln_BEA, D.ln_Coal, D.ln_Oil, D.ln_Gas, D.ln_CSI300, D.ln_ER, D.ln_Tmin, D.ln_Tmax, D.ln_AQI, and D.ln_BDI are cointegrated.

At this point, all data used to build the VAR model are stationary, i.e., they do not contain unit roots. Subsequently, the VAR model is ready to be constructed.

4.4 Building the VAR Model

4.4.1. Determining the Optimal Lag Order

In the Vector Autoregression (VAR) model, determining the optimal lag order is crucial, as it directly affects the model's reliability and predictive power. The larger the lag order, the smaller the degrees of freedom. Common criteria for determining the optimal lag order include the AIC and BIC criteria, with results shown in Table 4. Considering model simplicity, this paper uses the BIC criterion to determine the optimal lag order. Ultimately, the optimal lag order is determined to be 1. Therefore, a first-order autoregressive model, VAR(1), need to be constructed.

Table 4. Lag Order Selection

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1755.34				1.1e-11	3.14958	3.16651	3.19437
1	12514	28539	100	0.000	1.2e-22	-22.1303	-21.944	-21.6375*
2	12757.1	486.15	100	0.000	9.0e-23	-22.3855	-22.0299*	-21.4447
3	12873	231.9	100	0.000	8.7e-23*	-22.414*	-21.8891	-21.0252
4	12956.8	167.63*	100	0.000	9.0e-23	-22.3851	-21.6909	-20.5483

4.4.2 AR Root Test

The AR root test helps assess the stability of the VAR model. If the characteristic roots lie outside the unit circle, the model is unstable in long-term predictions, affecting its predictive ability. The test results are shown in Fig. 1, indicating that all roots lie within the unit circle, confirming the model's stability.

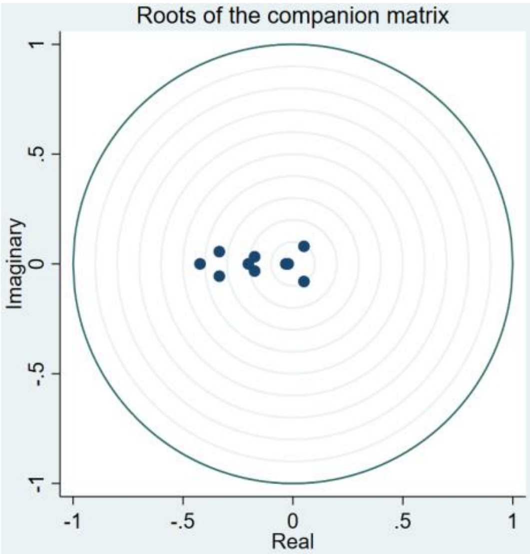


Figure 1. AR Root Test

4.5 Empirical Results and Analysis

The VAR(1) model constructed in this paper contains numerous coefficients, making it difficult to interpret their economic implications. Therefore, this paper primarily presents impulse response function graphs, analyzing the impact of various factors on BEA prices in terms of duration and direction in detail. In addition, because the data are daily, the period is set to 10 days, which is enough.

4.5.1 Impact of Energy Prices on BEA

1) Impact of Coal on BEA

According to the impulse response results of D.ln_BEA in Fig. 2, after a standard positive impulse, D.ln_BEA shows a slight increase within the 95% confidence interval. By the third to fourth period, the effect approaches zero, indicating that the impact of coal prices on BEA prices is positive but short-lived, disappearing by the fourth period.

2) Impact of Oil on BEA

According to the impulse response results of D.ln_BEA in Fig. 3, after a standard positive impulse, D.ln_BEA shows an increase within the 95% confidence interval. By the second period, the impact turns negative, and by the third to fourth period, the effect approaches zero, indicating that the impact of oil prices on BEA prices is initially positive but turns negative in the second period, disappearing by the fourth period.

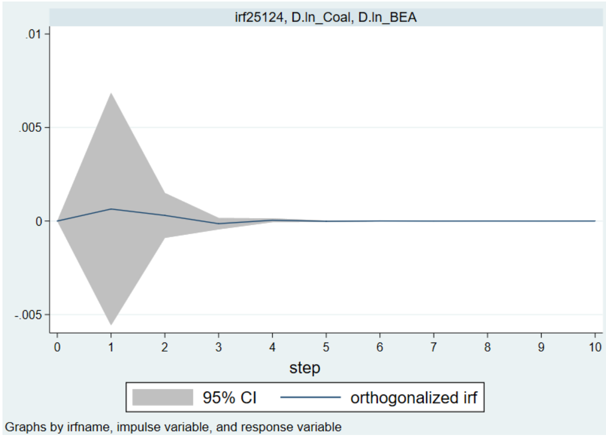


Figure 2. Impact of Coal on BEA**

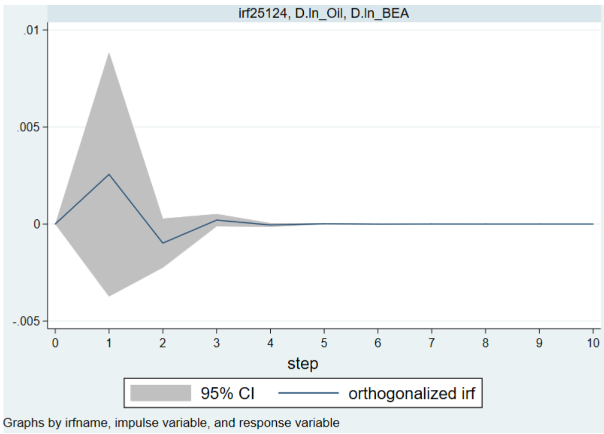


Figure 3. Impact of Oil on BEA

3) Impact of Gas on BEA

According to Fig. 4, after a standard positive impulse, D.ln_BEA shows a decrease within the 95% confidence interval. By the second period, the impact turns positive, and by the third to fourth period, the effect approaches zero, indicating that the impact of natural gas prices on BEA prices is initially negative but turns positive in the second period, disappearing by the fourth period.

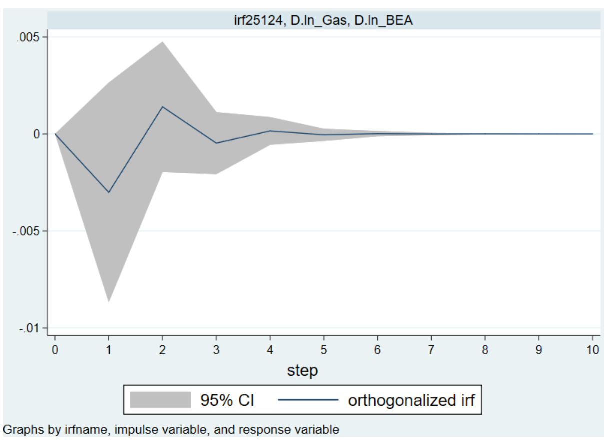


Figure 4. Impact of Gas on BEA**

4.5.2 Impact of Macroeconomic Conditions on BEA

1) Impact of CSI300 on BEA

According to Fig. 5, after a standard positive impulse to D.ln_CSI300, D.ln_BEA shows a decrease within the 95% confidence interval. By the second period, the impact turns slightly positive, and by the fourth period, the effect approaches zero, indicating that the impact of the CSI300 Index on BEA prices is initially negative but turns positive in the second period, disappearing by the fourth period.

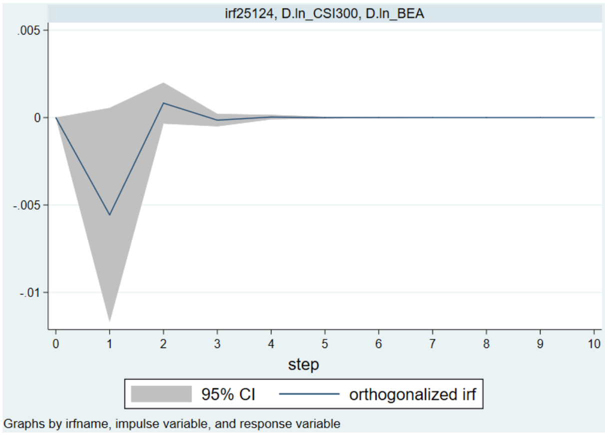


Figure 5. Impact of CSI300 on BEA

2) Impact of ER on BEA

According to Fig. 6, after a standard positive impulse to D.ln_ER, D.ln_BEA shows a decrease within the 95% confidence interval. By the second period, the impact turns slightly positive, and by the fourth period, the effect approaches zero, indicating that the impact of the exchange rate on BEA prices is initially negative but turns positive in the second period, disappearing by the fourth period.

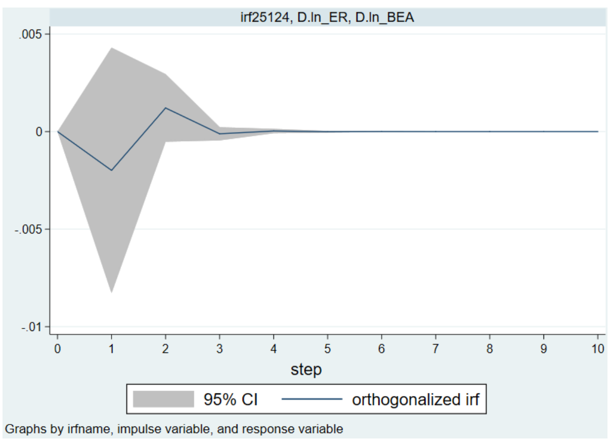


Figure 6. Impact of ER on BEA

4.5.3 Impact of Environmental Factors on BEA

1) Impact of AQI on BEA

According to Fig. 7, after a standard positive impulse to D.ln_AQI, D.ln_BEA shows a slight increase within the 95% confidence interval, followed by stabilization. By the fourth period, the effect approaches zero, indicating that the impact of the Air Quality Index on BEA prices is initially positive but stabilizes and disappears by the fourth period.

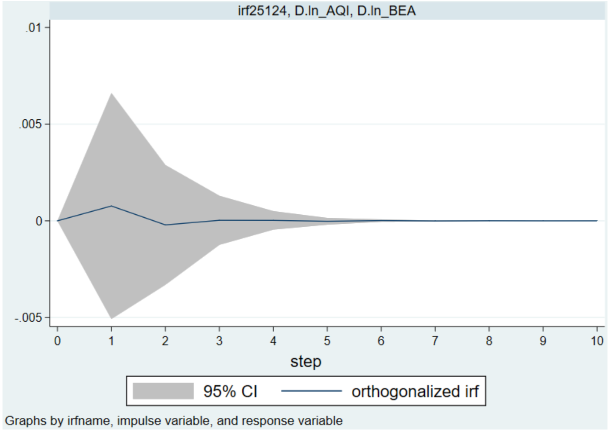


Figure 7. Impact of AQI on BEA

2) Impact of Tmin on BEA

According to Fig. 8, after a standard positive impulse to D.ln_Tmin, D.ln_BEA shows a negative impact within the 95% confidence interval, followed by stabilization. By the fifth period, the effect approaches zero, indicating that the impact of the minimum temperature on BEA prices is initially negative but stabilizes and disappears by the fifth period.

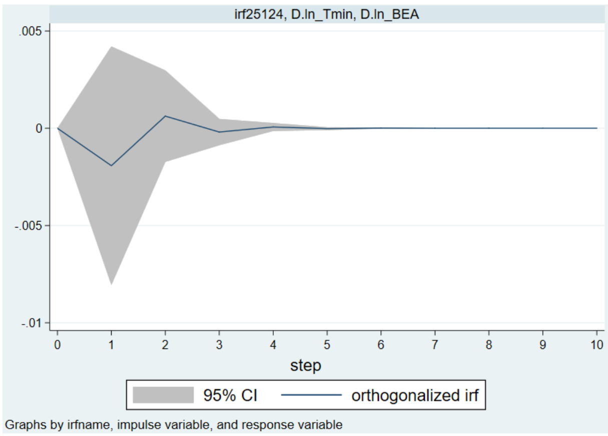


Figure 8. Impact of Tmin on BEA

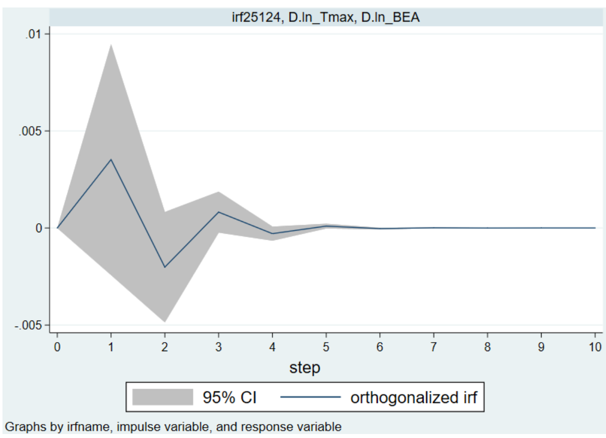


Figure 9. Impact of Tmax on BEA

3) Impact of Tmax on BEA

According to Fig. 9, after a standard positive impulse to D.ln_Tmax, D.ln_BEA shows a positive impact within the 95% confidence interval. By the second period, the impact turns negative, and by the sixth period, the effect approaches zero, indicating that the impact of the maximum temperature on BEA prices is initially positive but turns negative in the second period, disappearing by the sixth period.

4.5.4 Impact of Public Sentiment on BEA

According to Fig. 10, after a standard positive impulse to D.ln_BDI, D.ln_BEA shows a negative impact within the 95% confidence interval. By the second period, the impact turns slightly positive, and by the fourth period, the effect approaches zero, indicating that the impact of public sentiment on BEA prices is initially negative but turns positive in the second period, disappearing by the fourth period.

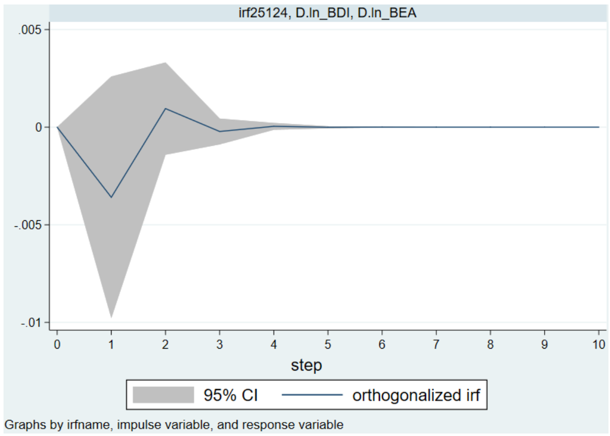
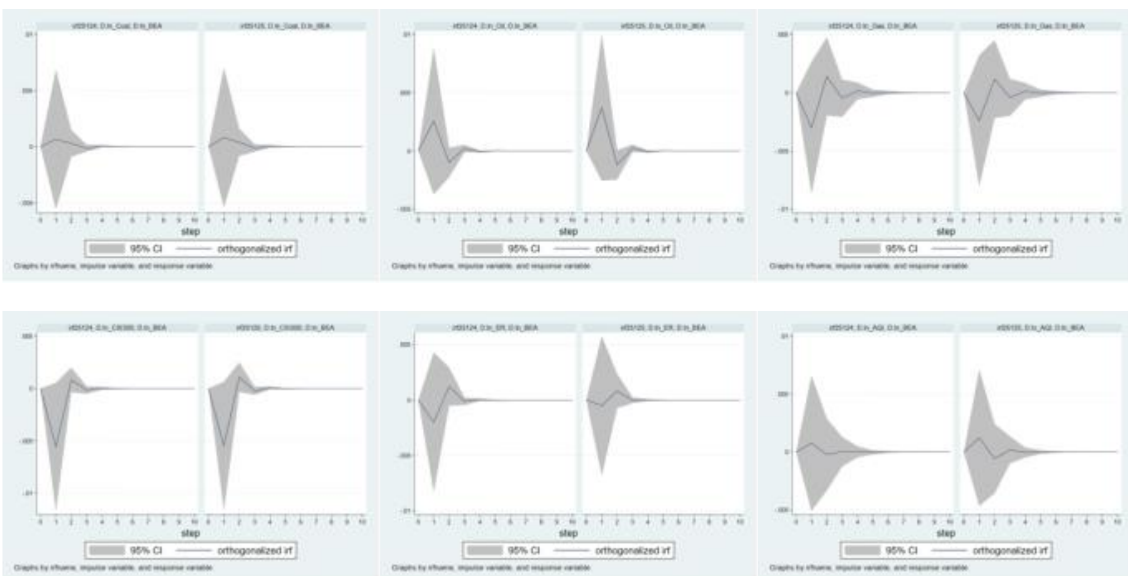


Figure 10. Impact of BDI on BEA

4.6 Robustness Test

Due to the unique nature of the VAR model—where the order of variables may affect the results—this paper reasonably changes the order of variables for the robustness testing. The impulse response graphs (before and after the order) change are shown in Fig. 11. The robustness analysis further confirms that the basic conclusions of this paper remain consistent.



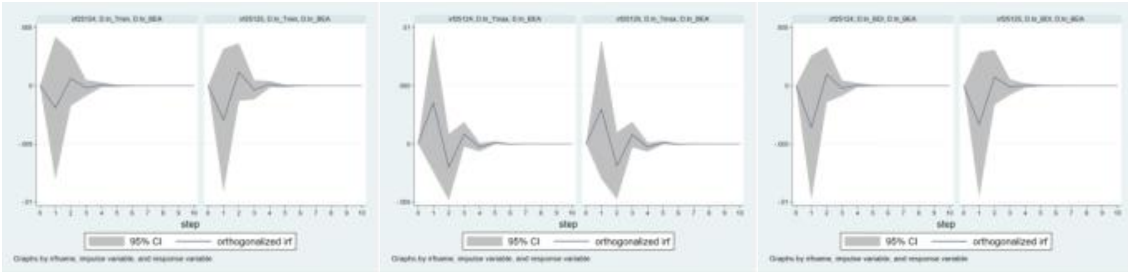


Figure 11. Robustness Test

5. Conclusions and Policy Recommendations

This paper constructs a first-order autoregressive model, VAR(1), using the average transaction price of Beijing Carbon Emission Allowances (BEA) as the research subject. It analyzes the influencing factors from four dimensions: energy prices, macroeconomic conditions, environmental factors, and public sentiment, and draws the following conclusions:

In terms of energy prices, coal and oil prices have a positive impact on BEA prices, while natural gas prices have a negative impact, with relatively longer-lasting fluctuations. This suggests that as coal and oil prices rise, BEA prices also rise, while rising natural gas prices lead to an initial decline followed by an increase in BEA prices. This may be because coal and oil are primary fossil fuels, and their price increases typically raise production costs, prompting companies to seek more carbon emission allowances to maintain production. This increased demand drives up carbon emission allowance prices. Market expectations may also play a role, as rising coal and oil prices lead to expectations of higher carbon costs, prompting companies to purchase more allowances in advance, further driving up prices. Natural gas, being a cleaner energy source, may lead companies to increase its use, reducing reliance on coal and oil. This shift may decrease demand for carbon emission allowances, lowering their prices. The longer-lasting fluctuations in natural gas prices may be related to market structure, supply chains, and policy changes. For example, the rise in natural gas prices may prompt more investment into the clean energy sector, reducing the demand for carbon emission allowance in the long run.

As for macroeconomic conditions, the CSI300 Index and exchange rate initially have a negative impact on BEA prices, followed by fluctuating recovery. The CSI300 Index reflects the overall performance of blue-chip stocks in China's A-share market. A decline in the index typically signals weaker economic growth expectations, leading companies to reduce production and, consequently, demand for carbon emission allowances. Additionally, a decline in the CSI300 Index may reduce investor confidence, making companies more cautious about future investments and production plans, leading to reduced demand for carbon emission allowances. Exchange rate fluctuations, particularly a depreciating RMB, may increase import costs. If companies rely on imported raw materials, higher costs may force them to reduce production or foreign investments, lowering demand for carbon emission allowances.

Speaking of environmental aspects, the Air Quality Index (AQI) and maximum temperature initially have a positive impact on BEA prices, followed by fluctuating recovery, while the minimum temperature has a negative impact. This may be because a high AQI indicates severe air pollution, prompting stricter environmental policies and reduced carbon emission allowance supply. High temperatures are often associated with high energy consumption, particularly in summer, leading to increased demand for BEA and higher prices. Conversely, lower minimum temperatures may indicate reduced energy demand, such as lower-than-expected heating needs, leading to decreased carbon emission allowance and lower demand for carbon emission allowances, resulting in lower prices of BEA.

Regarding public emotions, the Baidu Index initially has a negative impact on BEA prices, followed by fluctuating recovery. A low Baidu Index may indicate reduced public attention to the carbon market or carbon emission allowances, leading to weaker demand from market participants, particularly companies, which contribute to lower carbon emission allowance prices.

Considering the above research results, this paper proposes the following recommendations:

In the first place, develop flexible carbon emission policies. The government should adjust carbon emission policies in response to fluctuations in coal, oil, and natural gas prices to ensure market stability. Particularly when coal and oil prices rise, the government could provide incentives for companies to purchase carbon emission allowances in advance, preventing rapid price increases.

Subsequently, monitor macroeconomic conditions. Given the close relationship between stock market, exchange rate fluctuations and macroeconomic conditions, companies should closely monitor macroeconomic dynamics to adjust production and investment strategies promptly.

Thirdly, support the research and development of green technology. Increase support for the research and application of clean energy technologies to help companies improve energy efficiency, reduce production costs, and maintain stable demand for carbon emission allowances amid energy price fluctuations.

Finally, enhance public attention of the carbon market. Through education and publicity, increase public attention to the carbon market, enhance understanding and awareness of carbon emission allowances among companies and the public, and promote market activity.

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