Research on Price Transmission Mechanism of China Carbon Market and EU Carbon Market

Su Wang*
YINGDA INTERNATIONAL TRUST CO., LTD., Beijing, China
** Corresponding Author*

Abstract: In the background of continuous evolution in global carbon markets, the influence exerted by international market price fluctuations on the formation mechanism of China's domestic carbon pricing system has emerged as particularly pivotal for investors engaged in rational decision-making and risk mitigation. Leveraging daily transaction data from international carbon futures and domestic carbon allowances spanning from July 2021 to the end of 2024, this study constructs a Vector Autoregression (VAR) model to systematically investigate the dynamic interrelationships between global and domestic carbon market prices. Through comprehensive methodologies including Granger causality tests, impulse response analysis, and variance decomposition, the empirical analysis reveals two key findings: (1) China's carbon emission prices exhibit a unidirectional causal relationship with the European Union Allowance (EUA) prices, and (2) the international carbon futures market demonstrates a relatively weak and asymmetric influence on China's domestic carbon market, characterized by non-symmetrical dependency patterns. These discoveries underscore the strategic importance of domestic strategy frameworks and market mechanisms in shaping China's carbon pricing dynamics amid global market interconnections.

Keywords: Carbon Price; EU Carbon Market; Price Transmission Mechanism; VAR Model

1. Introduction

Global climate change has emerged as an urgent issue confronting countries worldwide, exerting severe impacts on ecosystems, economic development, and human livelihoods. To address climate change and reduce greenhouse gas emissions, countries around the globe have successively committed to implementing emission reduction measures, one of which is the establishment of carbon emission trading markets. Carbon emission markets regulate and control greenhouse gas emissions through market-oriented mechanisms, and actively encourage enterprises to adopt low-carbon technologies to strive for the achievement of emission reduction goals. In recent years, carbon emission markets worldwide have achieved certain results, providing an effective approach to addressing climate change[1]. As a country with relatively high carbon emissions, China bears an unshirkable responsibility in addressing global climate change and the government has actively promoted the construction of a carbon emission trading system[2], and set up pilot projects in multiple regions across the country to carry out carbon emission trading, striving to build a unified national carbon emission trading system market. With the continuous evolution of domestic and international carbon markets, the international carbon markets usually generates a transmission effect to the domestic carbon market; at the same time, the development of China's internal carbon market may also have an impact on the international carbon market. Because of this two-way price transmission mechanism, it is particularly important for this study to explore the interactive relationship between the two carbon markets.

2. Literature Review

With the advancement of global climate governance, carbon pricing mechanisms have increasingly become a key policy tool to promote low-carbon transformation. In terms of the correlation between macroeconomics and carbon prices, many scholars have provided empirical evidence. Lv(2019) based on multiple regression method, used correlation analysis and principal component analysis, and the results showed that European CER futures prices can significantly affect Guangdong's carbon trading prices[3]. Zhou(2019)constructed a VAR-VEC model to deeply explore the dynamic correlation between carbon emissions and energy prices, air quality, macroeconomic indicators, and carbon emission trading prices[4]. The analysis results showed that there is a long-term equilibrium relationship between carbon emission trading prices and the above indicators. Bai(2022) analyzed the carbon emission rights trading prices in eight carbon market pilots in Beijing, combined with different price fluctuation factors, and constructed an ARMA-GARCH model for empirical research[5]. The research results showed that among the ten selected economic indicators, some indicators and the daily closing data of European carbon emission rights trading have a significant impact on China's carbon emission rights trading prices.

Regarding the variable of the energy market, there are various different viewpoints and explanations in the academic circle. Liu(2021) constructed a VAR model and a DCC-GARCH model, and found through research that the impact of China's crude oil market on the carbon market and its duration are longer than those of the coking coal market[6]. In addition, Zhao (2018) conducted an empirical analysis based on data from five carbon pilot markets in China and found that thermal coal prices are negatively correlated with carbon prices, while fuel oil prices are positively correlated with carbon prices[7]. The observation results of Lü(2021) showed that coal price fluctuations have a significant correlation with carbon price changes in five Chinese carbon trading pilot markets[8]. Yan(2022) used VEC model, impulse response analysis, variance decomposition and other methods to deeply explore the transmission path between coal futures prices and carbon emission prices, and the research results revealed that there is a long-term equilibrium correlation between the two[9]. Lu(2018) evaluated the impact of carbon price fluctuations on domestic energy market prices from an international perspective, and pointed out that there is a long-term cointegration relationship between them, meaning that the long-term fluctuation trends of domestic energy prices and international carbon prices are consistent[10]. In addition, Aguiar-Conraria(2018) used an innovative multivariate wavelet analysis method to study the California carbon market and found that gasoline prices and carbon prices show a stable negative correlation within the annual cycle, while electricity prices and carbon prices show a positive correlation in the same cycle[11]. Wang(2022) combined the BK spillover index model on the basis of the DY spillover model, and found through research that there is a risk spillover effect between the carbon market and the power market, and the short-term intensity is significantly higher than the long-term[12]. Deng(2023) focused on the regional differences in energy consumption carbon emissions and their causes, and the research pointed out that the growth of population size, urbanization level, and per capita GDP will increase carbon emissions by increasing energy consumption; therefore, various regions in China need to adopt regionally differentiated emission reduction strategies according to their own characteristics[13].

Regarding the interaction between the atmospheric environment and related variables and the carbon market, Han(2019) conducted prediction research using the MIDAS-BP hybrid model, and the results showed that compared with other variables, carbon prices are more sensitive to changes in coal prices, temperature, and air quality[14]. Liu(2020) took the Beijing carbon trading pilot as a case, adopted the multi-factor GARCH-MIDAS model to identify the medium and long-term driving factors of carbon prices, and found that the air quality index is negatively correlated with carbon prices, while the changing trend of the Purchasing Managers' Index (PMI) of the manufacturing industry is consistent with carbon prices[15]. Rao(2019) focused on examining the characteristics and causes of price fluctuations in the carbon emission rights trading market, pointing out that price fluctuations show clustering effects and asymmetric characteristics, and identified the core factors that have a significant impact on price fluctuations in the Guangdong carbon market[16]. Li(2024) analyzed from the perspective of carbon pricing mechanism and believed that China's carbon market has adopted a follow-up pricing model, which helps to maintain the coordination and correlation between domestic carbon prices and international market prices[17]. Relevant research further explained the transmission mechanism of this linkage: changes in international carbon prices not only transmit market sentiment information, but also significantly affect traders' confidence, thereby exerting a profound impact on domestic carbon prices[18].

Since changes in international carbon emission rights prices will affect changes in China's carbon market prices, and China's current carbon market is still in the initial stage of development, it is urgent to deeply understand the internal mechanism of its international price transmission and formulate effective response measures. Only by ensuring the stable operation of the market and promoting the improvement of the system in a coordinated manner can we promote the healthy and orderly development of China's carbon market.

3. Sample Description

The EU Emissions Trading System (EU ETS) is the world’s longest-running and largest carbon emission trading system: it officially launched its first phase (2005-2007), initially covering key emission sectors such as energy and industry in EU member states; the second phase (2008-2012) aligned with the Kyoto Protocol’s emission reduction targets and expanded coverage; the third phase (2013-2020) introduced a Market Stability Reserve to smooth price fluctuations; since 2021, it has entered the fourth phase, further strengthening emission reduction goals and enhancing market flexibility and efficiency.

China’s carbon market follows the core path of “pilot first, gradual expansion”: in 2011, 7 provinces and cities including Beijing, Shanghai, and Guangdong launched local carbon trading pilots, accumulating basic experience in market operation; in July 2021, the National Carbon Emission Trading Market officially went online, initially covering only the power generation industry; subsequent efforts have focused on expanding sector coverage and improving mechanisms, and it is now moving toward a more mature national carbon trading system.

Figure 1 presents the price trends of the two markets, namely China’s carbon market (CEA) and the EU’s carbon market (EUA). In the initial phase from July 2021 to September 2021, both CEA and EUA showed volatility, but the price gap was significant: CEA fluctuated between 40-60 CNY, while EUA rose rapidly to a high of around 90 CNY. This gap reflects both the EU carbon market’s maturity advantage and the relatively weak price support of China’s carbon market in its early stage.

From October 2021 to September 2023, the two trends diverged sharply: EUA remained volatile in a high range of 70-90 CNY, with periodic fluctuations but staying at a relatively high level overall; CEA, by contrast, was relatively stable, fluctuating slightly in the 50-60 CNY range most of the time, highlighting the small price volatility, limited market activity, and weak external impact transmission of China’s carbon market in its early stage.

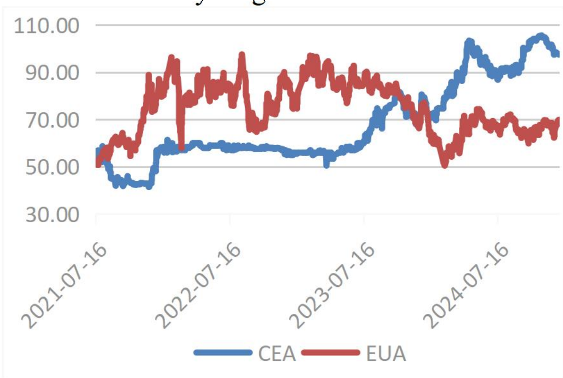

Figure 1. Price Trends

After October 2023, CEA entered an upward trajectory, climbing from around 50 CNY to over 90 CNY, narrowing the gap with EUA significantly and even approaching it periodically; during the same period, EUA remained high but became more volatile. This change not only reflects the growing activity of China’s carbon market but also may indicate that the transmission effect of international carbon price fluctuations on the domestic market is gradually emerging.

4. Methodology

Vector Autoregression(VAR) model is a widely adopted multi-equation modeling approach. For each current endogenous variable, this model conducts regression analysis by utilizing the lagged terms of all endogenous variables within the model, which can effectively capture the relationships among various endogenous variables and has been extensively adopted and applied in numerous research fields. This study chooses to use the VAR model, where the number of variables is n and the lag order is p, with the specific expressions as follows:

$$\boldsymbol{V_t = \alpha + \sum_{i=1}^{n} \beta_i V_{t-i} + \varepsilon_t} \quad (1)$$

$$\boldsymbol{V_t = [v_{1t}, v_{2t}, \cdots, v_{nt}]^T} \quad (2)$$

$$E(\varepsilon_t) = 0, E(\varepsilon_t \varepsilon_t^{'}) = \Omega \quad (3)$$

$$E(\varepsilon_t \varepsilon_s^{'}) = 0, s \neq t \quad (4)$$

Among them, Vt represents a homoscedastic stationary stochastic process composed of (p × 1) vectors, α denotes an (n × 1) dimensional constant vector, βi is a (p × p) coefficient matrix, Vt−i stands for the variable of the vector lagged by i orders, εt indicates the random disturbance term, and Ω represents an n × n symmetric positive definite matrix.

The Impulse Response Function can measure the degree of impact of information shocks on variables. By estimating the Impulse Response Function, the corresponding impulse response coefficients can be obtained in each VAR model. These coefficients reflect the response intensity of each endogenous variable in the model after being subjected to a unit shock from a specific variable. To more intuitively observe the impact path and degree of shocks, impulse response coefficients are usually represented graphically. These graphs show how a unit shock affects the current and future values of endogenous variables within a given period. By analyzing these graphs, one can understand the dynamic interactions between different variables and how shocks spread and dissipate in the system.

Variance Decomposition decomposes the variance of a system or model, analyzes the degree of influence of each factor or parameter on the system or model, and understands the contribution of each variable shock to the error[19]. This study will first adopt the Granger causality test to conduct a preliminary examination of the impact between international carbon prices and China's carbon prices, then establish a VAR model, and apply the impulse response function and variance decomposition to depict the mutual influence between the two prices. Since China's national carbon market was launched on July 16, 2021, this date is set as the starting point of the sample period, with the end date being December 31, 2024. After excluding data from inconsistent trading periods, a total of 829 valid data sets are obtained. To eliminate potential heteroscedasticity in the price time series, this study conducts logarithmic transformation on the variables: the logarithm of EUA is denoted as LNEUA, and the logarithm of CEA contract price is denoted as LNCEA.

5. Empirical Analysis

5.1 ADF Test

The ADF test evaluates whether the sequence is stationary by comparing its test statistic with a series of critical values based on different confidence levels and lag orders, and the test results are shown in Table 1. LNEUA is stationary, while LNCEA is non-stationary in its level form but becomes stationary after first-order differencing. Therefore, all subsequent analyses adopt the differenced data, which are denoted as DLNCEA and DLNEUA.

Table 1. Results of ADF Test

Variable	Orders	t	p	1% Critical Value	5% Critical Value	10% Critical Value
LNEUA	0	-3.084	0.028	-3.438	-2.865	-2.569
	1	-29.106	0.000	-3.438	-2.865	-2.569
LNCEA	0	-0.210	0.904	-3.438	-2.865	-2.569
	1	-34.620	0.000	-3.438	-2.865	-2.569

In this study, the optimal lag order is selected based on various lag length criteria including LR, FPE, AIC, SC, and HQ, and the lag order of the VAR model is finally determined to be 6, with the specific results presented in Table 2.

Table 2. Optimal Lag Order

Lag	LR	FPE	AIC	SC	HQ
0	NA	2.17E-13	-20.647	-20.625*	-20.639
1	31.128	2.12E-13	-20.671	-20.580	-20.635
2	32.696	2.06E-13	-20.697	-20.538	-20.635
3	16.253	2.07E-13	-20.694	-20.467	-20.606
4	6.419	2.11E-13	-20.674	-20.379	-20.559
5	21.079	2.09E-13	-20.681	-20.317	-20.539
6	141.992	1.67e-13*	-20.905*	-20.473	-20.737*
7	5.602	1.71E-13	-20.884	-20.384	-20.689
8	20.608	1.70E-13	-20.890	-20.322	-20.668

9	11.903	1.72E-13	-20.880	-20.244	-20.632
10	5.743	1.75E-13	-20.860	-20.155	-20.585
11	11.513	1.77E-13	-20.850	-20.077	-20.548
12	36.159*	1.71E-13	-20.886	-20.045	-20.558
13	9.134	1.73E-13	-20.871	-19.963	-20.517
14	10.127	1.75E-13	-20.859	-19.882	-20.478
15	5.034	1.79E-13	-20.837	-19.792	-20.430

5.2 Granger Causality Test

Before establishing the VAR model, the Granger causality test is first conducted on the variables to confirm whether there is a mutual influence between them. The results in Table 3 show that at the 10% significance level, the null hypothesis that there is no causal relationship between the two variables is rejected. Therefore, the VAR model can be constructed.

Table 3. Results of Granger Causality Test

Null Hypothesise	Obs	F-statistic	Prob.
DLNEUA does not Granger Cause DLNCEA	823	0.266	0.953
DLNCEA does not Granger Cause DLNEUA		2.01	0.063

5.3 VAR Model

The results of VAR estimation are shown in Table 4. The price transmission from China's carbon market to the EU carbon market exhibits a distinct unidirectional and lagged positive effect. As indicated in the table, changes in China's carbon price exert a significant positive impact on the EU carbon price with a 4-period lag, meaning that a 1% increase in China's carbon price will drive a 0.1155% rise in the EU carbon price after four periods. This medium-term transmission effect may stem from China's core position in the global supply chain— the increase in carbon costs caused by China's emission reduction policies gradually affects the carbon cost expectations of EU enterprises through international trade chains. Meanwhile, the transmission effects at other lag orders are insignificant, suggesting that the transmission is concentrated in a specific medium-term phase and reflecting the time lag in the transmission of policy effects.

In contrast, there is a complete absence of price transmission from the EU carbon market to China's carbon market. In the DLNCEA equation, all lagged terms of the EU carbon price (DLNEUA(-1) to DLNEUA(-6)) are statistically insignificant (maximum |t| = 1.52401 < 1.96). For instance, the coefficient of DLNEUA(-1) is -0.063587 (t = -1.18370). This asymmetry highlights the relative isolation of China's carbon market, which can be attributed to three main factors: first, China's capital account controls restrict the flow of international arbitrage capital; second, the domestic quota allocation mechanism, dominated by free allocation, weakens enterprises' sensitivity to external price signals; third, China's carbon market is still in the early stage of development with a relatively low level of market integration.

Figure 2 presents the characteristic roots of the VAR model. It can be observed that all characteristic root values lie within the unit circle, which indicates that the constructed VAR model has good stability, and the conclusions derived from this model are valid.

Table 4. Results of VAR Model

	DLNCEA	DLNEUA
DLNCEA(-1)	-0.182620**	-0.063587
	-0.03486	-0.05372
	[-5.23891]	[-1.18370]
DLNCEA(-2)	-0.065741*	-0.02301
	-0.03542	-0.05459
	[-1.85584]	[-0.42150]
DLNCEA(-3)	-0.01549	0.088941
	-0.03543	-0.0546
	[-0.43721]	[1.62901]
DLNCEA(-4)	0.022209	0.115500**
	-0.03544	-0.05461
	[0.62670]	[2.11493]
DLNCEA(-5)	-0.017808	0.017456
	-0.03543	-0.0546
	[-0.50261]	[0.31970]
DLNCEA(-6)	0.106544**	-0.076234
	-0.03482	-0.05366
	[3.05953]	[-1.42056]
DLNEUA(-1)	0.000742	-0.024669
	-0.02274	-0.03505
	[0.03263]	[-0.70382]
DLNEUA(-2)	0.0042	0.019191
	-0.02262	-0.03485
	[0.18571]	[0.55064]

DLNEUA(-3)	-0.006917	0.052967
	-0.02255	-0.03475
	[-0.30672]	[1.52401]
DLNEUA(-4)	-0.017791	0.016375
	-0.02253	-0.03471
	[-0.78981]	[0.47173]
DLNEUA(-5)	-0.000385	-0.107686**
	-0.02253	-0.03472
	[-0.01709]	[-3.10176]
DLNEUA(-6)	0.007152	-0.03573
	-0.02264	-0.03488
	[0.31595]	[-1.02425]
C	0.000802	0.000309
	-0.00063	-0.00097
	-0.182620**	-0.063587

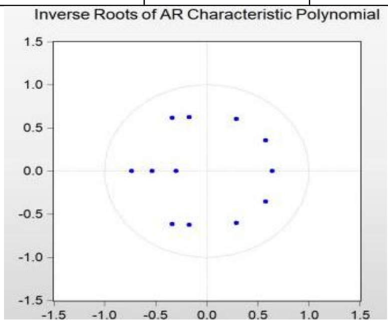

Figure 2. Scatter Plot of Characteristic Roots

5.4 Impulse Response and Variance Decomposition

To explore more precisely the dynamic linkages and hierarchical influence of variables between global and domestic carbon market prices, this paper employs the impulse response function for further in-depth analysis, with the results presented in Figure 3.

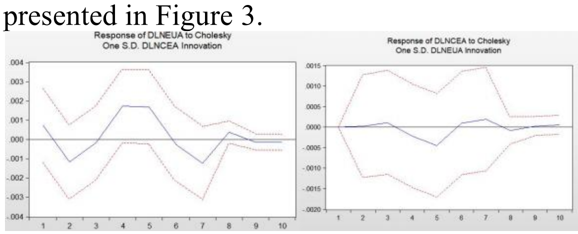

Figure 3. Impulse Response

Through a comparative analysis of the two impulse response function graphs, it can be observed that changes in China's carbon market price exert a significant price transmission effect on the global carbon market price. In the first graph, the red dashed line—representing the response of DLNEUA to shocks from DLNCEA—exhibits a large fluctuation amplitude with a peak response value of approximately 0.0035, coupled with a noticeable trough in the initial phase. This indicates that shocks from China's carbon market price have triggered relatively intense reactions in the global carbon market. In contrast, while the blue solid line—standing for the response of DLNCEA to shocks from DLNEUA—also reaches its peak in the 4th and 5th periods, its peak response value is merely 0.0015, and the overall fluctuation remains relatively mild. In the second graph, this trend is further corroborated: the red dashed line fluctuates drastically, whereas the blue solid line stays relatively stable. These findings demonstrate that in the price transmission mechanism, China's carbon market exerts a substantial influence on the global carbon market, while the impact of global carbon market price changes on China's carbon market price is relatively weak.

Further analysis reveals that the transmission of global carbon market price changes to China's carbon market price features higher intensity and more persistent effects. In comparison, the transmission effect of China's carbon market price changes on the global carbon market price appears rather limited. This discrepancy may be attributed to factors such as the maturity, market size, and policy environment of the global carbon market. As a more mature and open market, the global carbon market's price changes are more likely to attract worldwide attention and elicit responses, thereby exerting a notable impact on China's carbon market.

To conduct an in-depth analysis of the impact level of global carbon market prices on domestic carbon market prices, this paper carries out a variance decomposition analysis based on the VAR model, with detailed results presented in Table 5. The global carbon emission market exerts a significant price transmission effect on China's carbon emission market. The existence of such a transmission effect verifies that the global carbon market and China's carbon market are not isolated from each other but rather exhibit close linkage.

Table 5. Variance Decomposition

period	Variance Decomposition of S.E-DLNCEA	DLNCEA(%)	DLNEUA (%)	Variance Decomposition of S.E-DLNEUA	DLNCEA(%)	DLNEUA(%)
1	0.018	100.000	0.000	0.028	0.071	99.929
2	0.018	100.000	0.000	0.028	0.247	99.753

3	0.018	99.996	0.004	0.028	0.250	99.750
4	0.018	99.982	0.018	0.028	0.636	99.364
5	0.018	99.921	0.079	0.028	1.005	98.995
6	0.018	99.918	0.082	0.028	1.003	98.997
7	0.018	99.908	0.092	0.028	1.198	98.802
8	0.018	99.906	0.094	0.028	1.215	98.785
9	0.018	99.906	0.094	0.028	1.217	98.783
10	0.018	99.905	0.095	0.028	1.220	98.780

6. Conclusions and Suggestions

Based on the empirical analysis above, it can be observed that there exists a relatively stable equilibrium relationship between the price of EU Allowance (EUA) futures contracts and that of domestic emission allowance futures contracts over a long period. However, in the short term, the price transmission effect between these two prices exhibits a marked asymmetry. The Granger causality test shows that the price transmission between China's carbon market and the global carbon market presents a unidirectional guiding relationship: when the EUA price is subjected to external shocks, such shocks can be effectively transmitted to the domestic emission allowance market. Specifically, fluctuations in global carbon market prices exert a significant and relatively timely positive impact on the price of domestic emission allowance contracts. Conversely, the price transmission in the reverse direction shows a distinct lag. This indicates that China's carbon market has a delay in responding to global market price fluctuations, and the effectiveness of its reverse feedback mechanism is relatively weak.

Given that the global carbon market exerts a notable price transmission effect on China's carbon market while China's influence on the global carbon market remains relatively limited, China is placed in a disadvantageous position in terms of carbon price positioning. To enhance China's competitiveness in the global carbon market, it is imperative to learn from the mature carbon trading models of developed countries. This will not only help establish an independent carbon pricing mechanism but also effectively mitigate the operational risks faced by market participants. As the global carbon market is fraught with high uncertainties, China's carbon prices are highly susceptible to external impacts to a certain extent. To address global climate change issues and elevate the international influence of China's carbon market, the following recommendations are put forward:

To strengthen the regional synergy effect of the carbon market, efforts should be made to promote cross-regional connectivity with the carbon markets of neighboring countries. By establishing a regional carbon trading system, formulating unified market norms and regulatory mechanisms, and at the same time safeguarding the operational independence of each member state's carbon market, regional interconnection can not only enhance the global radiation capacity of China's carbon market but also expand the variety of carbon credit products available to enterprises within the region.

By collaborating with neighboring countries to advance joint carbon emission reduction initiatives, China can introduce its advantageous low-carbon technologies and mature emission reduction schemes into the environmental protection projects of other countries. This will help local enterprises improve energy efficiency and reduce greenhouse gas emissions. The carbon credit quotas generated through such cooperation can serve as a bilateral trade resource, which will not only assist partner countries in fulfilling their emission reduction commitments but also create new growth opportunities for the expansion of the global market supply and China's domestic low-carbon industry.

Establish a cooperation and exchange mechanism for carbon trading markets with surrounding countries. In terms of advancing regional carbon market capacity building, some neighboring countries have not yet established mature policy systems and technical support frameworks. Therefore, it is necessary to improve their carbon market development level through enhanced technical exchanges and experience sharing, thereby helping these countries build their own carbon trading systems.

To advance the internationalization process of the carbon market, accelerate the in-depth integration and connectivity between China's voluntary emission reduction mechanism and the global market, and actively participate in international carbon credit development and trading activities to strengthen the international recognition of domestic carbon credit products. Meanwhile, establish a cooperation mechanism featuring government guidance as the core, enterprises as the primary implementing entities, and market-oriented operation.

References

[1] Chen Fan, Gong Zhenting.Impact of China's Stock Market and EU Carbon Market on China's Carbon Market Price. Enterprise Economy,2023,42(03):48-57.

[2] Zhang Yun.Study on the Driving Factors of China's Carbon Trading Prices——From the Dual Perspectives of Market Fundamentals and Policy Information. Social Science Journal,2018, (01):111-120.

[3] Lv Jingye, Zhang Chao.Analysis on the influencing factors of China's carbon emission market price under the background of low carbon. Coal Economic Research,2019,39(05):31-37.

[4] Zhou K ,Li Y .Influencing factors and fluctuation characteristics of China’s carbon emission trading price. Physica A: Statistical Mechanics and its Applications,2019,524,459-474.

[5] Bai Qiang, Dong Jie, Tian Yuanchun.Study on the Volatility Characteristics and Influencing Factors of China's Carbon Emission Trading Prices. Statistics & Decision,2022,38(05):161-165.

[6] Liu Jianhe, Wen Congle, Liang Jiali.Research on Spillover Effects of Carbon Market and Energy Market Under the Background of Trade War. Journal of Industrial Technology and Economy,2021,40(07):57-64.

[7] Zhao Changhong, Zhang Mingming, Zhai Di.An Empirical Study on the Driving Factors of China's Carbon Price Based on the Pilot Carbon Market. Economic Forum,2018(12):136-141.

[8] Lv Jingye, Fan Xinya, Wu Haonan.Sensitivity Analysis of Factors Influencing Carbon Prices in China. Soft Science,2021,35(05):123-130.

[9] Yan Zhipeng, Yu ZeMin, Gu Xinlian.Research on Conduction Mechanism between Carbon Price and Coal Future Price in China. On Economic Problems,2022, (06):67-74.

[10]Lu Min, Cang Yuquan.Research on the Relationship between International Carbon Price Fluctuation and China's Energy Price. Price:Theory & Practice,2018,407(05):41-44.

[11]Aguiar Conraria Luís,Soares Maria Joana,Sousa Rita. California’s carbon market and energy prices. Philosophical Transactions: Mathematical, Physical and Engineering Sciences,2018,376(2126).

[12]Wang Xiping, Wang Wanchen.The Risk Spillover Effect Between Carbon and Power Market——Based on BK Spillover Model. Journal of Industrial Technology and Economy,2022,41(05):53-62.

[13]Deng Guangyao. Analysis of Regional Differences and Influencing Factors of Carbon Emissions from Energy Consumption . Statistics & Decision,2023,39(06):56-60.

[14]Han M ,Ding L ,Zhao X , et al.Forecasting carbon prices in the Shenzhen market, China: The role of mixed-frequency factors. Energy,2019, 171,69-76.

[15]Liu Junyang, Yang Fengjuan, Li Yabing.Study on the Long-Term Driving Factors Affecting the Volatility of China's Carbon Emission Trading Prices——Based on the Carbon Prices of the Beijing Environmental Exchange. Statistical Theory and Practice,2020, (03):11-16.

[16]Rao Xin.Research on Price Fluctuation Transmission Mechanism ofCarbon Emission Trading Market in Guangdong Province. China University of Geosciences (Beijing),2019.

[17]Li Mingliang.Study on the Driving Factors of China's Carbon Emission Trading Prices. PR World,2024(05):56-58.

[18]Yu Meiying.Analysis of the Factors Influencing the Carbon Price in China’sCarbon Market. Donghua University,2023.

[19]Liang Chunwen.Comparative study on price fluctuation of carbon emissions tradingbetween China and the EU. Jinan University,2018.

