Proceedings of the 8th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/103/2024BJ0217

Research on the Correlation Between Carbon Emission Rights and Energy Market: A Case Study of EUA and Oil Market

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Abstract: This study focuses on the importance of the relationship between carbon and oil in the context of global climate change and energy transition. In particular, this paper explores the link between fluctuations in the price of Brent crude oil in the United Kingdom and changes in the European Union Emission Allowances (EUA), which has significant implications for insight into energy market dynamics and policy making. This study uses an autoregressive (VAR) model to analyze the dynamic relationship between the European Union Emission allowances (EUA) market and the oil market from 2018 to 2024. Through Augmented Dickey-Fuller (ADF) stability test, the VAR model is established, the optimal lag order is determined, and the impulse response and Variance decomposition are analyzed. The results show that the EUA market has a short-term positive impact on the response of the oil market. But this effect has diminished over time, indicating the market's ability to self-regulate and stabilize. These findings provide new perspectives for understanding the interaction between global energy markets and environmental policy tools. The findings highlight the importance of considering these market dynamics when developing market strategies and environmental policies.

Keywords: EU emission quota market, oil market, dynamic relationship.

1. Introduction

In the context of global economic and environmental policy, the interaction between carbon emissions and oil markets has become a key area of research. The oil industry is an important part of global energy consumption, and its carbon dioxide emissions from extraction, processing and combustion are one of the main drivers of climate change. With the increasing global concern on greenhouse gas emissions, the petroleum industry is facing the increasingly severe pressure of emission reduction and the challenge of transformation and upgrading. The relationship between carbon and oil is crucial to understanding the dynamics of energy markets. Firstly, carbon emissions from the oil industry are directly related to the issue of global climate change, which affects the joint efforts of the international community to reduce greenhouse gas emissions. Secondly, the pursuit of a low-carbon economy on a global scale has promoted the adjustment of the energy structure, and the policy orientation and development trend of the oil industry have played a key role in the development of clean energy technologies. In addition, the establishment of a carbon trading market provides the oil industry with

DOI: 10.54254/2754-1169/103/2024BJ0217

an economic incentive to reduce emissions, which has a profound impact on enhancing its competitiveness and promoting sustainable development.

Chen Qinghua and Li Daoqing studies the correlation between the EU carbon quota market and the crude oil market, and discusses the relationship between the price fluctuations of the two [1]. Guo Fuchun and Pan Xiquan empirically analyzed the price fluctuation and risk measurement of the carbon market based on the price of the EU ETS futures contract, providing a quantitative assessment for understanding the risk characteristics of the carbon market [2]. Jixian Liu et al. takes the European Union as an example, this study analyzed the relationship between carbon futures and energy stock prices, and explored the implications for China's energy market and related policies [3]. Zhang Min et al. studied the impact of the development of new energy industry on the carbon market of the European Union through econometric methods, and analyzed how industrial policies affect the price and efficiency of the carbon market [4]. Li Qianglin et al. studied the volatility characteristics of international carbon futures prices and discussed the factors affecting the volatility of carbon futures prices [5]. Zheng Chunmei et al. analyzed the fluctuation characteristics of carbon emission right prices in the European Union and discussed the impact of market factors and policy changes on price fluctuations [6]. The next article uses two econometric models: the generalized Distribution of Error (GED) and generalized autoregressive Conditional heteroscedasticity (GARCH) models, and the value at risk (VaR) model, to quantify and analyze risk in the EU carbon futures market. The aim of the study is to assess the volatility of the carbon futures market and to predict the potential risks that may arise from extreme market events [7]. Zhao Jingwen studied the correlation between EU carbon futures prices and energy prices in her paper, providing an analysis for understanding the interaction between carbon market and energy market [8]. Based on EU ETS, Zhang Yuejun and Wei Yiming empirically analyzes the mean regression characteristics of international carbon futures prices and discusses the statistical rules of price fluctuations [9]. Nie Qiaoping and Xiang Fang reviewed relevant researches on EU ETS carbon emission rights futures, including market mechanism, price formation and risk management [10].

With the EU ETS entering its fourth phase. In the third phase, important reforms were carried out, including the introduction of market stability reserves (MSR) and auction mechanisms to improve market efficiency and stability of carbon prices. Nevertheless, the volatility of carbon prices during this period is still large, affecting the expectations and decisions of market participants. Phase 4 (2021-2030): It is currently in this phase and is characterized by more stringent emission reduction targets and market rules. This phase of reform includes a reduction in the allocation of free allowances, an increase in the proportion of auctions, and a greater focus on the risk of carbon leakage. However, there are relatively few specific studies in the existing literature on how these new changes affect the oil market, especially the volatility of crude oil futures prices. Compared with the previous three stages, market mechanisms and policy objectives have changed significantly. There are few studies on the specific impact of these new changes on the oil market, especially the volatility of crude oil futures, and how these changes reflect the dynamic relationship between the two through the VAR model.

In addition, for the fourth phase of EU ETS, this study aims to fill this gap by establishing a VAR model to analyze the daily rise and fall data of crude oil and carbon from 2018 to 2024, taking the rise and fall data of British Brent crude oil futures and EUA as an example to explore the interaction between the two. The methods of AR unit root graph, impulse response and variance decomposition are used to make up for the shortcomings of current research to some extent. The significance of this study is that it not only enriches the existing academic research, but also provides decision support for policy makers and energy industry practitioners. As the global goal of carbon neutrality advances, understanding and predicting the impact of carbon markets on oil prices has important practical implications for developing effective energy policies and responding to market changes. Through in-

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depth analysis, it is helpful to better grasp the future trend of the oil market and promote the sustainable development of energy.

2. Model Introduction

2.1. Model Construction

The Vector Autoregression (VAR) framework addresses the inconsistencies that can arise from the arbitrary selection of exogenous variables or the specification of lagged endogenous terms within an equation system. By formulating a model where each endogenous variable is expressed as a function of the previous values of all endogenous variables within the system, the VAR transcends the traditional univariate autoregressive approach, evolving into a multidimensional, vector-based autoregressive model that incorporates a set of interrelated time series. This model is adept at forecasting the behavior of interconnected time series and dissecting the propagation of shocks across variables, offering insights into the reverberations of economic perturbations on various economic indicators. The fundamental equation of the VAR model can be articulated as:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-1} + \varepsilon_t, t = 1,2, \dots T \tag{1}$$

Where α_i is the coefficient matrix with estimates, ε_t is the residual column vector, p s the maximum lag order.

2.2. Data Description

Futures trading on London's Intercontinental Exchange is the benchmark for market oil prices. The European Emissions Trading System is the world's largest carbon emissions trading market. Therefore, the daily data on the rise and fall of British Brent crude oil futures and the rise and fall of EUA from January 2, 2018 to July 19, 2024 are selected to eliminate missing data due to different dates. The data comes from the Investing website, and the statistical analysis software used for analysis is EViews13.

2.3. Descriptive Statistics

Daily raw percentage change data for EUA (European Emissions Allowance) and OIL were utilized for the analysis. The results show that the daily average raw percentage change of EUA is 0.001625, indicating that the overall EUA price shows a weak positive fluctuation trend. In comparison, OIL's average daily raw percentage change is 0.000465, showing lower average volatility. Looking at the medians, EUA's median percentage change is 0.001300, while OIL's median percentage change is 0.002100, which means OIL's fluctuations are more significant at the intermediate levels. Further observation shows that the maximum daily raw percentage change of EUA reached 0.175100, while the minimum change was -0.176500, showing that EUA prices have experienced relatively large fluctuations within a certain period of time. In comparison, OIL's maximum daily raw percentage change is 0.210200, which is slightly higher than EUA's maximum change, while its minimum change is -0.244000, which is also slightly lower than EUA's minimum change, indicating that the price fluctuations in the OIL market during certain periods It's more intense inside. In terms of standard deviation, the standard deviation of the daily raw percentage change of EUA is 0.028476, while the standard deviation of OIL is 0.025766. Although the difference between the two is not large, the standard deviation of EUA is slightly higher, indicating that the volatility of the EUA market is statistically more for dispersion.

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Table 1: eua market and oil market descriptive statistics result

	EUA_RAWPERCENTCHANGE	OIL_RAWPERCENTCHANGE
Mean	0.001625	0.000465
Median	0.001300	0.002100
Maximum	0.175100	0.210200
Minimum	-0.176500	-0.244000
Std. Dev.	0.028476	0.025766

3. Empirical analysis

3.1. Stationarity Test

The Augmented Dickey-Fuller (ADF) square root test was applied to the data ranging from 2018 to 2024. First, conduction a stationarity test on EUA. The ADF test statistic is -42.31035, which is much smaller than the critical value at the 1%, 5% and 10% significance levels. Therefore, rejecting the null hypothesis that it is stationary. Similarly, OIL's ADF test value is -38.77021, rejecting the null hypothesis, and the data is stable.

Table 2: EUA market ADF test

Augmented Dickey-Fuller test statistic			t-Statistic	Prob.*
			-42.31035	0.0001
Test critical values:	1% level		-2.566335	
	5% level		-1.941012	
	10% level		-1.616573	

Table 3: Oil market ADF test

Augmented Dickey-Fuller test statistic			t-Statistic	Prob.*
			-38.77021	0.0000
Test critical values:	1% level		-2.566335	
	5% level		-1.941012	
	10% level		-1.616573	

3.2. Construction of VAR Model and Selection of Optimal Lag Order

Determining the optimal lag order is a crucial step in constructing the time series model. The choice of lag order not only affects the fitting effect of the model, but also directly affects the prediction accuracy and generalization ability of the model. In this study, the AIC value is the lowest and the SC and HQ values are relatively low, indicating that the model with a lag order of 7 is both simple and effective, and can better balance the relationship between goodness of fit and complexity. At the same time, the prediction accuracy of the model is also considered. FPE is the final prediction error, and the smaller its value, the smaller the prediction error of the model. In this study, the FPE value reaches the minimum value when the lag order is 7. Finally, to ensure the robustness and statistical significance of the selected lag order, relevant statistical tests were conducted. By comparing the results of maximum likelihood estimation (LR) and F test under different lag orders, it is found that the model with a lag order of 7 is statistically better than the model with other lag orders (see Table 4). So, the optimal lag order is 7.

Table 4: Optimal lag order

Lag	LogL	LR	FPE	AIC	SC	HQ
0	7368.508	NA	5.27e-07	-8.780105	-8.773639*	-8.777710*
1	7374.091	11.14668	5.26e-07	-8.781992	-8.762593	-8.774806
2	7378.206	8.204612	5.26e-07	-8.782129	-8.749796	-8.770151
3	7384.686	12.90667	5.24e-07	-8.785085	-8.739820	-8.768317
4	7390.724	12.01098	5.23e-07	-8.787514	-8.729316	-8.765955
5	7395.373	9.235579	5.23e-07	-8.788287	-8.717156	-8.761936
6	7401.059	11.28523	5.22e-07	-8.790297	-8.706233	-8.759156
7	7406.026	9.844071*	5.21e-07*	-8.791449*	-8.694452	-8.755517
8	7406.563	1.064792	5.23e-07	-8.787322	-8.677393	-8.746599

3.3. AR Unit Root Diagram

In an autoregressive (AR) model, the inverse root of the characteristic polynomial (i.e. the root on the unit circle) directly determines the stability of the system. The criterion for stability is that all eigenroots must lie within the unit circle, i.e. their modulus (absolute value) must be less than 1. In this way, the system can be stabilized over time without continuous oscillations or divergences.

The distribution of these roots is therefore crucial for assessing the dynamic stability of the EUA market and the oil market. All the inverse roots are located in the unit circle, which indicates that both the EUA market and the oil market, their price changes will decay with time and eventually stabilize, showing that the market has an inherent regulatory mechanism and self-stabilizing ability (see Figure 1).

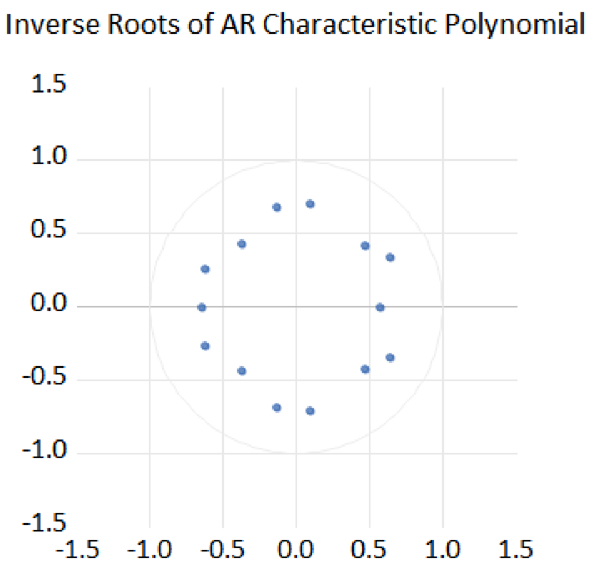

Figure 1: AR root graph

3.4. Impulse Response

As can be seen from the figure 2, after the initial shock, the change of Oil price has a positive impact on the change of EUA price, but the effect decreases with time. This suggests that volatility in the oil market can have a short-term impact on the carbon emission quota market, but this impact does not last long term. As the number of lag periods increases, the confidence interval gradually widens, which may imply that the uncertainty of the forecast is also increasing over time. Overall, this impulse

DOI: 10.54254/2754-1169/103/2024BJ0217

response analysis provides insight into the dynamic interaction between EUA and the Oil market, indicating that there is a degree of interdependence between them, but this dependence is temporary.

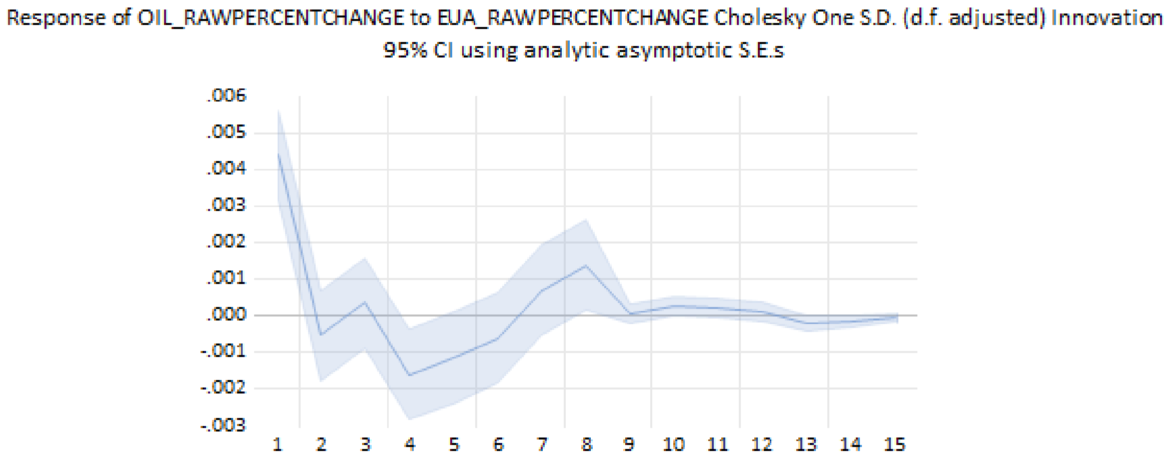

Figure 2: Impulse 1

As can be seen from the figure 3, when oil prices are hit, the EUA price response is positive in the short term, but the effect is small, almost close to zero. This effect gradually becomes more significant as the number of lag periods increases, although the response of the EUA price remains relatively small and does not exceed 0.003 during the lag period shown in the figure. This indicates that although the movement of oil prices has some effect on EUA prices, this effect is not strong in the short term.

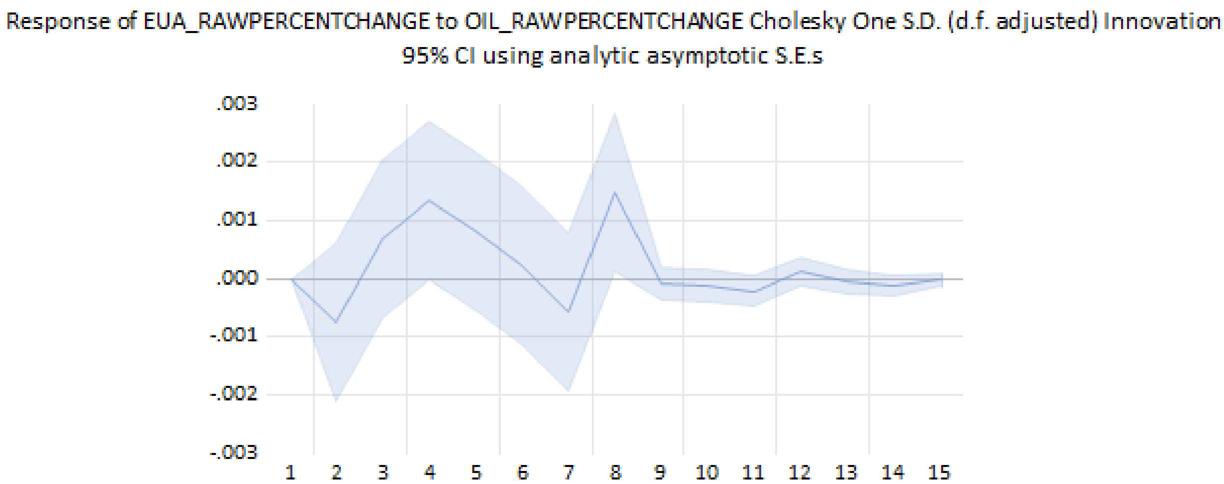

Figure 3: Impulse 2

3.5. Variance Decomposition

Through impulse response analysis of dynamic relationship between EUA market and oil market, variance decomposition technique is further used to explore their interaction. Variance decomposition analysis allows us to identify the ability of changes in one variable to explain changes in another variable at a given point in time. According to the variance decomposition results of EUA market, the influence of oil market on EUA market gradually decreases with the increase of lag time, and finally stabilizes at about 3.9%.

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Table 5: EUA market affect oil market variance decomposition result

Period	S.E.	EUA_RAWPERCENTCHANGE	OIL_RAWPERCENTCHANGE
1	0.028337	2.935130	97.06487
2	0.028362	2.964409	97.03559
3	0.028413	2.983315	97.01669
4	0.028445	3.359652	96.64035
5	0.028464	3.534690	96.46531
6	0.028553	3.586606	96.41339
7	0.028582	3.642884	96.35712
8	0.028621	3.919940	96.08006
9	0.028621	3.920578	96.07942
10	0.028622	3.931216	96.06878
11	0.028623	3.937374	96.06263
12	0.028624	3.939335	96.06067
13	0.028624	3.945024	96.05498
14	0.028624	3.948159	96.05184
15	0.028625	3.948226	96.05177

Following the impulse response analysis of the interaction between the oil market and the EUA market, the dynamic relationship of oil was further analyzed through variance decomposition. Variance decomposition results reveal the extent to which oil market price changes are affected by EUA market. As the lag time grew, the proportion of oil market affected by EUA market eventually stabilized at approximately 0.75%. This ratio shows that the EUA market's long-term contribution to oil market price fluctuations is limited.

Table 6: Oil market affects EUA market variance decomposition result

Period	S.E.	EUA_RAWPERCENTCHANGE	OIL_RAWPERCENTCHANGE
1	0.028337	100.0000	0.000000
2	0.028362	99.93264	0.067364
3	0.028413	99.87647	0.123527
4	0.028445	99.65580	0.344196
5	0.028464	99.57009	0.429905
6	0.028553	99.56700	0.433000
7	0.028582	99.52947	0.470526
8	0.028621	99.25791	0.742092
9	0.028621	99.25695	0.743053
10	0.028622	99.25506	0.744937
11	0.028623	99.24922	0.750775
12	0.028624	99.24713	0.752866
13	0.028624	99.24666	0.753343
14	0.028624	99.24454	0.755457
15	0.028625	99.24452	0.755477

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4. Conclusion

In this study, an autoregressive (AR) model was used to analyze the dynamic relationship between the EU emission allowances (EUA) market and the oil market between 2018 and 2024. By considering Akaike information quantity (AIC), Schwartz information quantity (SC), Hanke-Quine information quantity (HQ) and final prediction error (FPE), the optimal lag order is 7. This choice not only ensures the simplicity and validity of the model, but also verifies its statistical superiority and robustness through maximum likelihood estimation (LR) and F tests. Impulse response analysis reveals the short-term positive impact of the OIL market on the EUA market, but this impact decreases over time, indicating that there is a certain dynamic interaction between the two markets, but this dependence is temporary. This interaction is further quantified by variance decomposition analysis, which shows that the EUA market has limited ability to explain changes in the OIL market. Combining the analysis results of this study, the conclusions drawn not only highlight the short-term dynamic interaction that exists between the EUA market and the oil market, but also highlight the inherent stability and regulatory capacity of the respective markets. These findings have important implications for a deeper understanding of the workings of global energy markets, the impact of environmental policy tools, and their combined effects in combating climate change.

This study analyzes the dynamic relationship between the EU emission quota market and the oil market from 2018 to 2024 through an autoregressive model. Although the conclusion is drawn that there is a short-term positive impact between the two markets and the impact decreases with time, there are still some limitations. First, the time span of the study limits the observation of long-term trends, and the linear assumptions of the model may fail to capture the non-linear characteristics of the market. Secondly, although the optimal lag order is determined by various information criteria, different order choices may have significant differences on the model results. In addition, while statistical tests validate the robustness of the model, more tests may be needed to ensure the generalisability of the results. At the same time, the research mainly focuses on short-term market interaction, and the analysis of long-term policy impact and market structural changes is insufficient. In addition, while the findings have implications for understanding the effects of global energy markets and environmental policy tools, further work is needed to translate them into concrete policy recommendations. Finally, limitations in data sources may also affect the broad applicability of the results. Future research could expand the time horizon, consider nonlinear models, explore more influencing factors, and validate them in a broader market and policy context to provide more comprehensive and in-depth insights.

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