



Assessing the impact of European Union Emissions Trading System on crude oil, maritime transportation, and EU's carbon markets: a spillover analysis

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Abstract

This paper investigates the impact of the European Union Emissions Trading System (EU ETS) policy on the relationship between the crude oil market, the crude oil maritime transportation market, and the EU's carbon market, focusing on the period before and after the inclusion of maritime emissions in 2024. The study examines both the interactions among returns and volatility of markets. The results indicate that no significant spillover effect was observed among three markets during Phase 3 (pre-policy transition). Nevertheless, following a policy shift (Phase 4), there was a marked increase in the degree of correlation and volatility spillover. The findings highlight that EU ETS policy plays a key role in the relations among these three markets. Entering Phase 4, the crude oil market exhibits a positive link with the crude oil maritime transportation market and displays a negative relationship with the EU's carbon market. Additionally, crude oil maritime transportation and EU's carbon markets exhibit a two-way volatility spillover. The primary driver of fluctuations across these three markets is identified as crude oil. These results suggest that policymakers should account for the interdependencies among these markets when formulating policies. Meanwhile, maritime operators can reduce risks by using carbon futures to hedge against price fluctuations in carbon and crude oil markets, supporting sustainable development in the shipping industry.

Keywords Crude oil market · Crude oil maritime transportation market · EU's carbon market · Spillover effects · Policy recommendations

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1 Introduction

Greenhouse gas emissions are among the most pressing environmental challenges, contributing to global warming. It has continued to attract widespread attention in recent years. The maritime industry accounts for roughly 90% of international trade transportation and produces a significant amount of carbon emissions annually (Schwartz et al., 2020). Shipping activities have a significant impact on environmental sustainability (Sun et al., 2025). The International Maritime Organization (IMO) stated in the “Fourth Greenhouse Gas Research Report” that if maritime transportation carbon emissions are not controlled, it is estimated that by 2050, it will increase by 90–130% compared with 2008 (Meng et al., 2022). This estimate further emphasizes the urgency of reducing carbon emissions from maritime transportation and promotes research and implementation of sustainable development strategies in the maritime industry. To achieve this goal, the maritime industry is expected to adopt a series of measures, including technological retrofitting of vessels, the development and utilization of cleaner fuels, and operational measures focusing on route optimization (Sun et al., 2024a). Meanwhile, the integration of maritime transport into the carbon trading scheme is also a hot topic of discussion.

The European Union Emissions Trading System (EU ETS), dominant in global carbon trading, continues to influence worldwide carbon policies. EU ETS has had a profound impact on power generation, heating production, and energy-intensive industries (Zeng et al., 2021). Starting in 2024, the EU will formally integrate the maritime sector into the EU ETS, which will oblige shipping firms to cover their own CO₂ emissions during business trips. Shipping companies will need to submit one carbon allowance (EUA) for each ton of CO₂ emitted. This policy change is expected to affect shipping companies’ operational costs and regulatory requirements. Shipping industry’s inclusion in EU ETS not only imposes direct compliance costs on carriers but also introduces systemic risks to global trade. Additional carbon costs may prompt fuel switching, such as from high-emission fuels to cleaner-burning alternatives, or operational adjustments, such as slow steaming, which could change the balance between freight rates, crude oil demand and carbon pricing.

The role of crude oil in the shipping industry cannot be ignored. Crude oil is not only the primary energy source for shipping (Geman & Smith, 2012), it also significantly influences the carbon market. (Ji et al., 2018; Le et al., 2024). One side, crude oil consumption directly affects industrial carbon emissions, which in turn impacts carbon market trading activities (Dutta, 2018). Besides, marine fuel oil is the largest contributor to carbon emissions in the shipping sector (Maitra et al., 2020). Oil price fluctuations directly impact fuel costs, which in turn influence freight cost (Drobetz et al., 2012). Against this background, carbon market could be a step closer to enhancing the link crude oil and shipping markets. This means that fluctuations in crude oil prices not only affect shipping costs but may also influence carbon market trading activities through changes in market demand, causing interconnected dynamics. Such interconnected dynamics create potential spillover effects across markets. Understanding these spillovers is critical for policymakers to address inflationary pressure on energy prices and for shipping companies to hedge cross-market risks. Shipping companies must determine if carbon hedging strategies can mitigate exposure to oil price shocks, while energy traders need to anticipate how EU ETS-driven demand shifts might reshape crude oil market fundamentals. This complex interplay underscores the necessity of quantifying spillover mechanisms to inform both regulatory design and corporate risk management frameworks in an increasingly carbon-constrained global economy.

From the point of view of oil, this paper discusses the effect of EU ETS on marine transport. It includes two aspects. (1) Whether EU ETS has an impact on the shipping industry? This important policy change is often overlooked in empirical studies, but it is the focus of this paper. To address this, the data are divided into two sample periods corresponding to Phase 3 and Phase 4 of the EU ETS. The reasons for this division are twofold. First, EU ETS has evolved through four phases. The initial two phases (2005–2007 and 2008–2012) were experimental, utilizing free allocation of allowances with weak volatility in carbon prices, making them unsuitable for studying market volatility. However, Phase 3 (2013–2020) witnessed significant increases in carbon prices due to reduced total carbon emissions and the replacement of free allowances with auctions, making it an ideal period for studying market volatility. Second, the EU suggested that marine emissions be integrated into the fourth Phase of the EU ETS (2021–2030). By comparing the sample groups from Phases 3 and 4, the impact of this inclusion on the maritime industry can be accurately identified. (2) How do spillover effects among crude oil, crude oil maritime transportation, and EU's carbon markets perform as EU ETS enters Phase 4 (with the shipping sector incorporated into EU ETS)? Current research on spillover effects primarily focuses on the crude oil and carbon markets (Ren et al., 2022), and marine transport markets (Fei et al., 2020; Chen et al., 2023). Whether there are linkages between these three markets and how the interaction is unexplored. Meng et al. (2023) proposed a cascading information flow pathway from the carbon market through the energy sector to the maritime transport sector, based on signal theory. However, their study remains theoretical. It deals only with two targets, namely carbon and shipping markets, while the influence of energy markets in this context is not yet fully explored. This paper examines whether spillovers among markets can verify whether the crude oil market plays the role of an intermediary channel for information transfer. It extends the theoretical framework of Meng et al. (2023). In addition, this paper jointly considers mean and volatility spillovers. This paper reveals the complex interaction mechanism among the three markets with a more comprehensive analysis.

This paper follows this structure: Section 2 examines existing studies. The methods and data sources are described in Section 3. Spillover effects among crude oil, crude oil maritime transportation and EU's carbon markets are analyzed in Section 4, alongside a discussion of empirical results. At last, we give conclusion and suggestion in Section 5.

2 Literature review

2.1 Interactions between crude oil and crude oil maritime transportation markets

Existing research frequently examines the link among crude oil and crude oil maritime transportation markets, highlighting that crude oil prices are a pivotal factor influencing the latter (Gavrilidis et al., 2018). Fei et al. (2020) applied an improved R/S model to investigate BDTI's volatility, taking into account the effects of significant events. They found that crude oil market volatility is a key factor influencing BDTI fluctuations. Dai et al. (2020) utilized BEKK-GARCH model to analyze volatility spillovers in crude oil and shipping markets, revealing that volatility primarily transmits from the former to the latter. Riaz et al. (2023) reached the same conclusion using the spillover index method. Angelopoulos et al. (2020) used dynamic analysis to investigate commodity and transport markets, showing that oil prices serve as a precursor to changes in tanker freight rates.

Moreover, the impact of crude oil on shipping differs across various time periods. Li et al. (2018) applied MF-CCA and MF-DPXA approaches for analyzing oil price impacts on BDTI. While oil prices significantly affect the BDTI, they have discovered that the correlation is time dependent. Maitra et al. (2020) accounted for time-varying factors and found stronger connections between the two markets when economic policies changed.

Though there are many researches on the transfer relation of crude oil and its maritime transportation markets based on time varying factors and economy events, it has neglected to consider the impact of policy change on them.

2.2 Interactions between crude oil and carbon markets

Following the creation of EU's carbon market, several scholars have explored links between energy and EU's carbon markets, indicating feedback mechanisms from carbon to energy sectors. (Dai et al., 2021; Li et al., 2021). In the energy market, crude oil prices are considered a key driver of carbon pricing (Gong et al., 2021; Le et al., 2024). But Zhang and Sun (2016) studied interactions between carbon and energy markets with the VAR-BEKK-GARCH model. Their results indicated that no significant spillover effect during EU ETS Phase 2. This may mean that policy differences across EU ETS phases influence the dynamics between carbon and energy markets. Wang and Guo (2018) proposed that that it is essential to consider policy elements while studying the spillover effects related to the EU's carbon market, especially once the EU ETS enters its third phase. Dai et al. (2021) applied a multiscale information network spillover analysis framework to examine how carbon markets and energy markets interacted during Phase 3. In the latter part of the third phase, they discovered a notable influence on the energy sector, whereas such an effect was not observed in the earlier stage of Phase 3. Therefore, our study takes into account the impact of EU ETS policies in different phases on spillover effects.

2.3 Interactions between crude oil maritime transportation and carbon markets

Studies focusing on the transfer of information between carbon and crude oil maritime transportation markets remain scarce. Meng et al. (2023) applied wavelet alongside DY index to investigate how volatility transfers occurred between marine market and carbon market. Their study revealed effects between carbon, dry bulk shipping markets and fuel markets, but no such spillover was found with the crude oil maritime transportation market. But their data covered only Phases 2 and 3 of the EU ETS. The policy change that included maritime emissions in Phase 4 of the EU ETS was not considered in their study. This policy change is the focus of this paper.

2.4 Research methods of spillover effects

Spillover is a kind of impact on the value of assets in different markets. Typically, spillover effects are transmitted through changes in asset returns and their volatility. Spillover effects are generally divided into two main categories: mean spillover and volatility spillover. Mean spillover is the influence of the returns across the various markets, and it may be positive or negative. Volatility spillover pertains to how price fluctuations in one market influence on another. The direction of volatility spillover indicates how information transmits. When market A influences market B through volatility spillover,

it means that data from market A -like shocks or price fluctuations- are relayed to market B, leading to market B's price fluctuations (Zeng et al., 2021). Given that volatility signifies asset risk, the volatility spillover effect fundamentally pertains to how risk is communicated across different markets.

Various research methods are utilized to examine spillover effects across markets, such as VAR model, Multivariate GARCH models, TVP-VAR models, and the spillover index.

The TVP-VAR model and spillover index are frequently employed to evaluate dynamic spillovers among different markets. For example, Riaz et al. (2023) applied the spillover index to examine evolving volatility interactions linking the oil and shipping sectors.

The GARCH class encompasses approaches like BEKK-GARCH, DCC-GARCH, and DECO-GARCH. Among these, DCC-GARCH and DECO-GARCH frameworks are frequently utilized to understand relationships across markets. For instance, Chen et al. (2020) utilized DCC-GARCH framework to capture time-varying relationships between the crude oil, new energy, and rare earth sectors. Kang et al. (2017) employed the DECO-GARCH approach to measure dynamic correlations among six commodity futures markets. Their study, in combination with the spillover index, identified directional dynamic spillovers across these markets.

The VAR model and BEKK-GARCH model are often combined to compare spillover effects across different periods and multiple markets. BEKK-GARCH estimates are consistent in methodology with VAR outcomes and are also simpler in computation than in the case of other GARCH models. (Sun et al., 2018). Although primarily used to measure static spillover effects, combining the VAR and BEKK-GARCH models enables more comprehensive and multidimensional analysis. Song et al. (2022) assessed the mean and volatility spillover interactions in China's carbon market and several energy sectors, using the VAR-BEKK-GARCH framework. Zhao et al. (2023) explored spillover effects among two carbon trading platforms and six Nordic power markets by applying the VAR-BEKK-GARCH model.

2.5 Review of the research status

Most studies have focused on spillovers linking crude oil and crude oil maritime transportation markets, along with its connections to the carbon market. Crude oil prices are widely regarded as a key determinant of tanker freight rates and carbon prices. Additionally, significant economic events and policy changes throughout various EU ETS phases played a critical role in shaping spillover effects across markets. However, while economic events have been extensively studied by researchers, policy changes remain underexplored. Notably, the integration of maritime emissions into Phase 4 is a new policy that has yet to be thoroughly addressed in empirical studies.

It highlights the central role of crude oil market in linking maritime transportation market and the EU's carbon market, along with the substantial policy changes influencing the shipping industry due to the EU ETS's transition into its fourth phase. This study specifically examines the mean and volatility spillover effects between crude oil, crude oil maritime transportation, and EU's carbon markets. By utilizing VAR-BEKK-GARCH model, the spillover effects among these three markets during Phases 3 and 4 of the EU ETS are compared and analyzed to provide a holistic understanding of their interaction mechanisms.

3 Materials and methods

3.1 VAR model

This paper employs VAR model to compute mean spillovers among markets, creating a methodological foundation for subsequent volatility spillover analysis. To establish a valid VAR model, stationarity of the data must be confirmed through preliminary testing, typically employing the Augmented Dickey-Fuller (ADF) method as the primary approach for assessing stationarity. The core mathematical formulation for VAR model can be stated below:

$$R_t = C + A_1 R_{t-1} + A_2 R_{t-2} + \cdots + A_k R_{t-k} + \varepsilon_t \quad (1)$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \quad (2)$$

The state of the internal variable vector at time t is represented as R_t . The constant term is represented as C , with the estimated coefficients incorporated into matrix A . It is assumed that the residual vector ε_t follows a zero-mean distribution with a constant variance. The lag order, denoted by k , is determined through various criteria, including Akaike Information Criterion (AIC), Schwarz Criterion (SC), and so on, based on accessible market data at time $t-I$, represented as I_{t-1} . AIC and SC have been extensively employed in existing studies (Jia et al., 2024; Ma et al., 2021).

Each variable in the VAR model is explained by its own lag and the lag of other variables, so that VAR can grasp the complicated dynamical relations among them.

3.2 BEKK-GARCH model

Engle and Kroner (1995) developed a new GARCH model, which is called BEKK-GARCH. The method ensures that the variable covariance matrix is positively definite, and the estimation quantity is decreased. In this paper, it is employed to calculate volatility spillovers between markets, enabling a comprehensive assessment of the transmission and persistence of market volatility. Confirm the existence of ARCH by the ARCH-LM test. This is essential for constructing BEKK-GARCH model.

$$e_{i,t} = v_{i,t} h_{i,t} \quad (3)$$

$$v_{i,t} \sim N(0,1) \quad (4)$$

$$h_{i,t} = c_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (5)$$

$$H_t = C^T C + A^T e_{t-1} e_{t-1}^T A + B^T H_{t-1} B \quad (6)$$

Formula (3) sets up the relation of the residual term $e_{i,t}$ and conditional variance, $h_{i,t}$. The residue $v_{i,t}$ adheres to a standard normal distribution. We make use of the coefficients α and β . H_t denotes the conditional variance–covariance matrix, while C represents the lower triangular matrix. Additionally, A and B are square arrays.

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix} \quad (7)$$

$$C = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix} \quad (8)$$

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \quad (9)$$

$$B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \quad (10)$$

Within the matrix H_t , we can find $h_{ii,t}$ represents the conditional variances of each market's return. The value of $h_{i,j(i \neq j)}$ signifies conditional covariances between market i and j . The elements of matrix A capture the impact of historical shocks on current volatility, reflecting the ARCH effect. Among them, a_{ii} reflects the effect of brief external shocks on variations. The off-diagonal components of matrix A denote the transmission of shocks across markets. Matrix B represents the GARCH modulus, demonstrating the influence on previous volatility on current volatility. b_{ii} represents the persistence of the volatility of the three markets themselves (GARCH effect). Non-diagonal components of Matrix B indicate the cross-market volatility spillovers.

Wald test is applied to validate volatility spillover, thereby evaluating robustness of BEKK-GARCH model estimations. If $a_{ij} = b_{ij} = 0$, it suggests no significant volatility spillover effect from market j to market i .

3.3 Sample selection and data

This paper selects three variables to represent their corresponding markets: Brent crude oil futures prices, Baltic Dirty Tanker Index (BDTI), and EUA futures prices. Brent futures contracts have high liquidity in international markets, which makes its prices a good measure of global oil market changes. Currently, over 65% of global crude oil is priced based on Brent crude oil price (Maitra et al., 2020). Many researchers use it as a representative indicator for empirical analysis of the crude oil market (Chen et al., 2020; Gong et al., 2021). BDTI provides a comprehensive assessment of the cost of transporting crude oil on 11 international routes, making it a reliable indicator of the overall crude oil transportation market. Many related studies are based on this index (Drobetz et al., 2012; Riaz et al., 2023). It is selected here to represent price trends in the crude oil transportation market. In addition, EUA futures prices, administered by EU ETS, represent the most authoritative carbon trading prices (Zeng et al., 2021; Zhao et al., 2023). It reflects not only the EU's carbon market but also the outlook for future carbon emission demand and policy changes. The firm's decision to buy carbon permits is driven by EU's carbon markets value and future prospects. Thus, it is appropriate to use its futures price to represent the EU's carbon

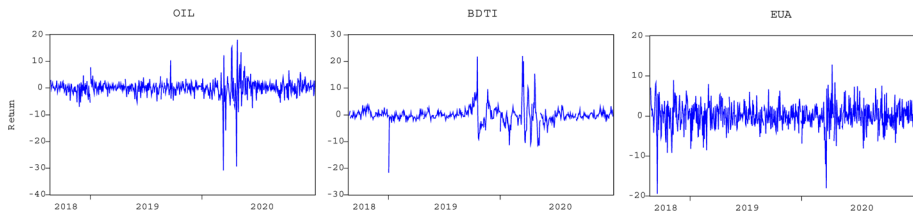


Fig. 1 Day returns of crude oil, its maritime transportation and EU's carbon market (Aug. 21, 2018—Dec. 31, 2020). Note: The data breaks were caused by selection which covered the dates when all three markets had transactions

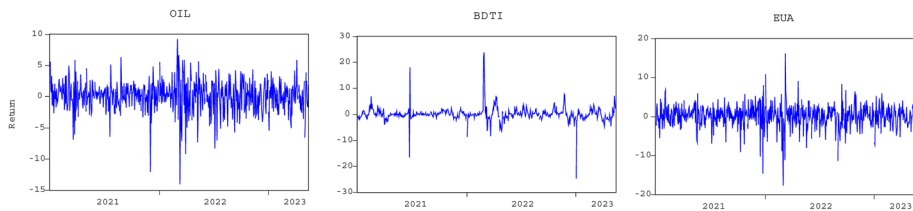


Fig. 2 Day returns of crude oil, its maritime transportation and EU's carbon market (Jan 1, 2021—May15, 2023). Note: The data breaks were caused by selection which covered the dates when all three markets had transactions

market. Both oil and carbon futures prices are derived from Wind database (www.wind.com.cn). The BDTI is issued by Baltic Exchange with Clarkson Research (www.clarksons.net.cn).

This paper selects the daily data of three indicators to analyze, because high-frequency daily returns are preferred in spillover analyses to resolve short-term market reactions while mitigating oversmoothing. The data for this paper is taken from two sample periods: August 21, 2018 to December 31, 2020 and January 1, 2021 to May 15, 2023. The paper selects only the dates when all three markets had transactions, resulting in 587 observations for each group. Missing values and outliers are addressed using data from the preceding trading day.

The original price data demonstrate high volatility and considerable randomness. To preserve data structure stability, data processing is conducted through the logarithmic difference methodology (Wen et al., 2019), resulting in processed data being considered as the return (R_t):

$$R_t = \left[(\ln P_t) - \ln(P_{t-1}) \right] \times 100 \quad (11)$$

Here, P is an index or price at time t , and a market value of $t-1$.

Figures 1 and 2 show the temporal progression of daily returns for three groups of data over two sample periods, in order to observe volatility clustering. It should be noted that this paper only selects the dates when all three markets have transactions. However, the analysis software EViews 10.0 will still use continuous time series as the abscissa when forming figures. For this reason, the figures exhibit data breaks.

Both Tables 1 and 2 show a statistical description of revenue from these three markets in both sample periods. The results show the characteristic characteristics of

Table 1 Descriptive statistics of returns (Aug. 21, 2018—Dec. 31, 2020)

Variable	$R_{1,t}(\text{OIL})$	$R_{2,t}(\text{BDTI})$	$R_{3,t}(\text{EUA})$
Mean	-0.0595	-0.0905	0.0942
Max	18.0884	22.0309	12.8057
Min	-30.8558	-21.5783	-19.4437
Std.Dev	3.2995	3.1989	3.2408
Skewness	-1.9943	0.8769	-0.6325
Kurtosis	29.6981	18.5613	7.0788
Jarque-Bera	17,792.3200*** (0.0000)	5987.6750*** (0.0000)	445.2723*** (0.0000)
ADF	-18.5373*** (0.0000)	-11.4592*** (0.0000)	-24.8609*** (0.0000)
PP	-22.84147*** (0.0000)	-10.92766 (0.0000)	-24.88617 (0.0000)
ARCH-LM	19.8265*** (0.0000)	23.8222*** (0.0000)	10.3835*** (0.0013)

***, **, * are significant at the values of 1%, 5% and 10%. Value in parentheses indicates P-value

Table 2 Descriptive statistics of returns (Jan 1, 2021—May15, 2023)

Variable	$R_{1,t}(\text{OIL})$	$R_{2,t}(\text{BDTI})$	$R_{3,t}(\text{EUA})$
Mean	0.0682	0.1463	0.1584
Max	9.2601	23.8076	16.1942
Min	-14.0407	-24.5686	-17.7230
Std.Dev	2.5064	2.7252	3.0291
Skewness	-0.6439	1.1439	-0.6307
Kurtosis	5.9332	37.3927	7.8212
Jarque-Bera	250.5696*** (0.0000)	29,009.22*** (0.0000)	606.3769*** (0.0000)
ADF	-19.0817*** (0.0000)	-10.2136*** (0.0000)	-25.3357*** (0.0000)
PP	-23.40396 (0.0000)	-15.52225 (0.0000)	-25.36679 (0.0000)
ARCH-LM	6.7535*** (0.0094)	61.7858*** (0.0000)	25.6403*** (0.0000)

***, **, * are significant at the values of 1%, 5% and 10%. Value in parentheses indicates P-value

leptokurtosis and fat-tail, as shown by their kurtosis values above 3. Moreover, the Jarque—Berke statistic has statistical significance for every return, which suggests that no return follows the normal distribution. On the basis of ADF and PP (Phillips & Perron) results, the returns for the two sets of samples were 1% significant, indicative of their stability. In addition, the ARCH-LM analysis showed a marked ARCH impact of 1% level in all three markets. Thus, using the BEKK-GARCH approach to analyze the impact of volatility is justified..

Table 3 Estimation results of VAR (1) model. (Aug. 21, 2018—Dec. 31, 2020)

	$R_{1,t}(\text{OIL})$	$R_{2,t}(\text{BDTI})$	$R_{3,t}(\text{EUA})$
$R_{1,t}(-1)$	0.0394[0.0430]	-0.0288[0.0324]	-0.0380[0.0421]
$R_{2,t}(-1)$	-0.0814*[0.0432]	0.6291***[0.0326]	-0.0678[0.0423]
$R_{3,t}(-1)$	0.0121[0.0432]	0.0263[0.0326]	-0.0199[0.0424]
Constant	-0.0706[0.1363]	-0.0376[0.1028]	0.0758[0.1337]

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *. Value inside a square bracket represents a standard error

Table 4 Estimates for the VAR (1) model. (Jan 1, 2021—May15, 2023)

	$R_{1,t}(\text{OIL})$	$R_{2,t}(\text{BDTI})$	$R_{3,t}(\text{EUA})$
$R_{1,t}(-1)$	0.0467[0.0411]	-0.0516[0.0401]	-0.0053[0.0501]
$R_{2,t}(-1)$	0.0777**[0.0379]	0.4619***[0.0370]	-0.0845*[0.0462]
$R_{3,t}(-1)$	-0.0711**[0.0342]	0.0001[0.0334]	-0.0582[0.0417]
Constant	0.0561[0.1030]	0.0849[0.1005]	0.1842[0.1255]

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *. Value inside a square bracket represents a standard error

4 Empirical results and discussion

4.1 Mean spillover effect analysis

This paper employs a VAR model to compute mean spillovers across markets. AIC and SC criteria serve as tools to identify optimal lag order k for VAR model. For the first sample period, the lag orders suggested by AIC and SC are 4 and 1, respectively. Following the SC criterion to select a more parsimonious specification, a lag 1-order VAR model is adopted. Similarly, $k = 1$ is chosen for the second sample period using the same procedure. Outcomes of VAR(1) are presented in Tables 3 and 4.

This paper analyzes the mean spillovers among the three markets using data from Tables 3 and 4, focusing on the positive and negative correlations among the crude oil market, crude oil maritime transportation market, and EU's carbon market. The discussion of intermarket correlations relies on off-diagonal coefficients and their significance in the tables.

Observing the outcomes in Table 3, in the crude oil equation, the lagged returns of the crude oil maritime transportation market exhibit show a significant mean spillover effect within a 10% confidence level. Coefficient for maritime transportation market in the crude oil equation is negative, indicating a negative correlation between the two markets. It is consistent with existing research findings (Michail & Melas, 2020). COVID-19's impact and the steep decline in oil prices might account for the negative relationship (Riaz et al., 2023). In a low oil price environment, transportation costs not only decrease, but lower oil prices also encourage refineries to purchase more crude oil. It will result in a rise in the need for crude oil imports, resulting in a rise in the cost of shipping. COVID-19 outbreak has disrupted the supply chain, which has exacerbated the steep increase in cargo charges.

The results shown in Table 4 show in crude oil equation, significant mean spillovers from both the crude oil maritime transportation and EU's carbon markets. The maritime transportation market coefficient is positive, while the EU's carbon market coefficient is negative, indicating a positive association across the crude oil and its maritime

transportation markets and a negative association among crude oil and EU's carbon markets. Besides, a 5%-significant mean spillover originating in maritime transportation market and directed toward EU's carbon market, marked by a negative coefficient, signals a negative correlation between these two markets.

Entering the second sample period, as the global economy recovered in the second period, rising oil prices increased bunker fuel costs, directly impacting shipping costs (Chen et al., 2023). It shifts the crude oil-maritime transportation relationship to positive correlation. In addition, higher oil prices also suppressed economic activity, reducing energy consumption and carbon allowance demand, thus depressing carbon prices (Le et al., 2024; Li et al., 2021). Attention should be given to the negative relationship between crude oil maritime transportation and EU's carbon markets. It reflects the dual impact of oil prices on transportation costs and carbon pricing. It is related to the green transition in the shipping industry driven by the EU ETS. Companies now include carbon costs in crude oil shipments. To hedge risks, they often purchase EUAs in advance.

4.2 Volatility spillover effect analysis

The BEKK-GARCH model is applied to study volatility transfer pathways. Results are presented in Tables 5 and 6. The components in Matrix *A* measure the ARCH effect, which is indicative of short-term stability in different markets. On the other hand, the elements in matrix *B* measure the GARCH effect, representing long-term persistence between markets. This research aims at enhancing the understanding of inter-market volatility spillovers. Thus, this section concentrates on the GARCH effect, which reflects volatility spillovers between markets.

Observing Table 5, during the first sample period, the diagonal elements a_{ii} in matrix *A* show 1% significance suggesting that each market is subject to its own short-term shocks. Likewise, b_{ii} also exhibit 1% significance, implying that each market is subject to its enduring volatility persistence. In the case of crude oil and EU's carbon markets, the estimated values of a_{11} and a_{33} are smaller than b_{11} and b_{33} , suggesting that the own long-term volatility persistence outweighs short-term effects in these two markets. However, the crude oil maritime transportation market shows the opposite pattern.

Non-diagonal elements in matrix *A* reveal short-term volatility interactions among the three markets. Specifically, a_{12} and a_{13} are 1%-significant, suggesting short-term shocks from crude oil maritime transportation market and EU's carbon market to crude oil market, respectively. Besides, shocks of crude oil maritime transportation market to EU's carbon market are 10%-significant (a_{32}). But no significant long-term volatility spillovers are observed among the three markets during this period.

Table 6 presents BEKK-GARCH model outcomes during the second sample period. Just as in the first sample period's findings, each market is affected by its own short-term and long-term volatility persistence. The diagonal elements in matrices *A* and *B* are 1%-significant, which indicates that unexpected events in each market may cause greater volatility in their own market prices. The coefficient a_{12} is 10%-significant, suggesting the crude oil maritime transportation market short-term shocks will propagate to crude oil market, while this impact is one-way. It can be attributed to tanker freight, as freight is a crucial part of crude oil supply costs, especially when tanker hauling capacity is tight.

In the second sample period, significant volatility spillovers are observed between different markets, as shown by the nondiagonal factors in matrix *B*. Specifically, at the 1% significance b_{23} and b_{32} are significant. It indicates a significant volatility spillover exists

Table 5 BEKK-GARCH model results. (Aug. 21, 2018—Dec. 31, 2020)

Variable	Coefficient	T-statistic	P-value
c_{11}	0.4677***	5.7291	0.0000
c_{21}	0.1368	0.3234	0.7464
c_{22}	0.9182***	9.2610	0.0000
c_{31}	0.3428***	2.7958	0.0052
c_{32}	0.0070	0.0399	0.9681
c_{33}	0.0000	-0.0001	1.0000
a_{11}	0.2686***	6.5718	0.0000
a_{12}	-0.1945***	-4.1845	0.0000
a_{13}	0.1487***	3.9329	0.0001
a_{21}	0.0622	1.2146	0.2245
a_{22}	1.0653***	14.4002	0.0000
a_{23}	-0.0803	-1.3898	0.1646
a_{31}	0.0207	0.7844	0.4328
a_{32}	0.0801*	2.1243	0.0336
a_{33}	-0.1817***	-4.9925	0.0000
b_{11}	0.9426***	81.9255	0.0000
b_{12}	0.0061	0.1532	0.8782
b_{13}	-0.0114	-0.8938	0.3714
b_{21}	-0.0575	-1.3215	0.1863
b_{22}	0.2496***	3.6234	0.0003
b_{23}	0.0735	1.5879	0.1123
b_{31}	-0.0067	-0.9471	0.3436
b_{32}	-0.0009	-0.0382	0.9695
b_{33}	0.9794***	118.1159	0.0000

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and * respectively

among crude oil maritime transportation and EU's carbon markets. It is different from the research conclusion of Meng et al. (2023). But this may be because their research data mainly focuses on Phases 2 and 3 of the EU ETS. Our research shows that entering Phase 4, the two-way spillovers among EU's carbon and maritime transportation markets turns significant. This is attributable to the extension of the EU ETS. This change in policy radically changes the relationship between the markets. Before the Phase 4, carbon costs were external to shipping operations, limiting direct feedback between freight rates and EUA prices. However, Phase 4's inclusion of maritime emissions internalizes these costs, creating a bidirectional dependency where freight rate adjustments directly affect carbon allowance demand, and vice versa.

In concrete terms, companies in the maritime industry, such as ship owners and operators, are exposed to the EU ETS and its pricing mechanisms. They may transfer these costs to cargo owners, resulting in a significant increase in freight rates (Xue & Lai, 2023). As a result, fluctuations in the EU's carbon market inevitably get transmitted to the maritime transportation market. Looking from the opposite direction, outside factors and internal supply demand dynamics severely impact the crude oil maritime transportation market. This impact will be reflected in the volatility of crude oil maritime transportation rates (Fei et al., 2020). The volatility of transportation prices affects the operational modes of ships.

Table 6 BEKK-GARCH model results. (Jan 1, 2021—May 15, 2023)

Variable	Coefficient	T-statistic	P-value
c_{11}	-0.3419*	-1.8789	0.0603
c_{21}	0.6301***	6.5217	0.0000
c_{22}	0.0743	0.1803	0.8569
c_{31}	1.6676***	6.3522	0.0000
c_{32}	0.1977	0.2323	0.8163
c_{33}	0.0387	0.0653	0.9479
a_{11}	0.2391***	4.8648	0.0000
a_{12}	-0.0577*	-1.7559	0.0791
a_{13}	-0.0206	-0.3595	0.7192
a_{21}	-0.0448	-0.8722	0.3831
a_{22}	1.1266***	13.4046	0.0000
a_{23}	-0.0480	-0.8745	0.3819
a_{31}	-0.0201	-0.5710	0.5680
a_{32}	0.0173	0.7465	0.4554
a_{33}	-0.1581***	-2.8727	0.0041
b_{11}	0.9425***	42.1608	0.0000
b_{12}	0.0461	1.5549	0.1200
b_{13}	-0.0078	-0.2254	0.8217
b_{21}	0.1210**	2.5378	0.0112
b_{22}	0.2922***	3.8502	0.0001
b_{23}	-0.1854***	-3.3991	0.0007
b_{31}	0.1300***	3.8653	0.0001
b_{32}	-0.1228***	-5.3607	0.0000
b_{33}	0.7920***	15.6615	0.0000

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *

When prices rise, maritime operators reduce fuel consumption and save costs by slowing down their speed or optimizing their routes. At the same time, fuel consumption is key in determining the amount of carbon emissions. EU ETS has strict limits on the total amount of emission allowances. Changes in carbon allowances demand will cause fluctuations in carbon prices. the volatility of the maritime transportation market extends to the EU's carbon market.

Additionally, b_{21} and b_{31} are 1%-significant and 5%-significant, respectively, indicating volatility spillover effects from crude oil market to both crude oil maritime transportation and EU's carbon markets. According to b_{21} and b_{32} , an indirect way of volatility spillover on "crude oil market → crude oil maritime transportation market → EU's carbon market" is found. Similarly, by combining b_{31} and b_{23} , we interpret another indirect volatility spillover way on "crude oil market → EU's carbon market → crude oil maritime transportation market". This indicates that oil prices are a key source of volatility spillover. It is consistent with existing literature conclusions (Le et al., 2024; Riaz et al., 2023). It close link between crude oil and shipping markets is attributed to cost-push effect (Khan et al., 2021). Fuel costs not only make up a substantial portion of operating expenses but also cause fluctuations in crude oil transportation costs, thereby affecting the overall crude oil transportation market. Additionally, existing research confirms the

significant influence of crude oil market on EU's carbon market (Ji et al., 2018). It is not surprising. The fluctuation of crude oil as a significant criterion for energy prices has a significant impact on the manufacturing costs of energy-intensive businesses, while the change in carbon price is a non-negligible part of production expenses. The result further complements the hypothesis proposed by Meng et al. (2023), that the energy market may be not a mediator in information transmission but rather a net transmitter of volatility spillover effects.

Observed spillover dynamics can be traced to interconnected economic mechanisms rooted in energy market theory. Rising oil prices exert a dual pressure: they directly increase bunker fuel costs, compelling shipping firms to adopt operational adjustments like slow steaming or fuel switching, which simultaneously alter freight rate volatility and carbon allowance demand (Khan et al., 2021; Xue & Lai, 2023). According to Clarksons (2025), alternative fuel has continued to play a prominent role, and there has been a return to LNG dual fuel technology dominating. Deceleration has become the primary means of reducing fuel consumption on the operational side. This is consistent with our finding of a spillover effect of increased BDTI-EUA volatility, as fuel substitution and deceleration reduce both fuel costs and carbon allowance requirements. It aligns with the research outcomes of Sun et al. (2024b). The two-way linkage is further amplified by EU ETS compliance costs, which incentivize firms to pass on expenses through freight surcharges, thereby tightening the coupling between carbon and shipping markets. Additionally, including maritime transport into Phase 4 of the EU ETS is likely to increase speculation on EUA forward and cargo derivatives as traders exploit price discrepancies in the newly interconnected markets. These mechanisms collectively align with the 'Policy-Operation-Finance' nexus framework, where regulatory interventions (EU ETS) cascade through operational decisions into cross-market financial risks, offering a systemic explanation for the spillover patterns.

Finally, Wald test is carried out to evaluate the robust performance of the volatility spillover. The test results are presented in Tables 7 and 8. In Table 7, Wald test outcomes are consistent with the direction of short-term market shocks between the first sample period. Similarly, in the second sample period (Table 8), the Wald test shows significant volatility spillovers between crude oil and its maritime transportation markets, and also between crude oil maritime transportation and EU's carbon markets. Additionally, only EU's carbon market to crude oil market shows volatility spillover effects.

Wald's results are consistent with those of BEKK-GARCH and stress their robust performance.

Table 7 Results of Wald test (Aug. 21, 2018—Dec. 31, 2020)

Markets	Hypothesis	Wald statistics
Crude oil and crude oil maritime transportation markets	$a_{12} = b_{12} = 0$	8.79659***
	$a_{21} = b_{21} = 0$	0.88296
Crude oil and EU's carbon markets	$a_{13} = b_{13} = 0$	11.40766***
	$a_{31} = b_{31} = 0$	1.82567
Crude oil maritime transportation and EU's carbon markets	$a_{23} = b_{23} = 0$	1.29125
	$a_{32} = b_{32} = 0$	2.27047*

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *

Table 8 Results of Wald test. (Jan 1, 2021—May 15, 2023)

Markets	Hypothesis	Wald statistics
Crude oil and crude oil maritime transportation markets	$a_{12} = b_{12} = 0$	2.42776*
	$a_{21} = b_{21} = 0$	4.22077**
Crude oil and EU's carbon markets	$a_{13} = b_{13} = 0$	0.276635
	$a_{31} = b_{31} = 0$	8.17293***
Crude oil maritime transportation and EU's carbon markets	$a_{23} = b_{23} = 0$	12.31720***
	$a_{32} = b_{32} = 0$	14.71838***

Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *

5 Conclusions and recommendations

This paper explores the effect of EU ETS on maritime transportation in terms of crude oil transport. The paper deals with two key questions: whether EU ETS affects the shipping industry, and how spillover effects between crude oil, crude oil maritime transportation, and EU's carbon markets manifest as the EU ETS enters its fourth phase, which now includes the shipping industry. In order to investigate those dynamics, we use VAR-BEKK-GARCH model to assess the influence of mean and volatility on maritime transportation, as well as the EU's carbon market. The mean spillover results are discussed to determine the positive and negative correlations at the level of market returns, while volatility spillover results help recognize the direction of risk transmission among markets. Furthermore, the robust performance of the model was evaluated by Wald tests. Our empirical results show that there are inter-related changes in the markets that are influenced by marine emissions policy.

The results show that there has been a marked change in the relationship of the market since the policy change, with a marked variation in mean and volatility spillovers across the three markets. During Phase 3, there was no noticeable spillover in three markets. In Phase 4, however, both mean and volatility spillover effects became significant. This shift indicates that the maritime sector is gradually adapting to the 'green policies' introduced by the EU ETS.

The findings show links among crude oil, crude oil maritime transportation, and EU's carbon markets. The mean spillover outcomes among markets indicate crude oil market is positively correlated with crude oil maritime transportation market and negatively correlated with EU's carbon market. Additionally, a negative correlation exists among crude oil maritime transportation and EU's carbon markets. Two major spillover trends are identified in this research: Crude oil is the source of volatility spillovers to both crude oil maritime transportation and EU's carbon markets, with two-way volatility spillovers between crude oil maritime transportation and EU's carbon markets. These results provide a decision-making basis for shipping risk management. For example, rising crude oil prices demonstrate risk transmission to both EU's carbon and crude oil maritime transportation markets. Based on the negative correlation with the EU's carbon market, EUA futures are expected to decline. Based on the positive correlation with the crude oil maritime transportation market, transportation costs are expected to increase. During this period, shipping operators can control transportation costs by purchasing EUAs through carbon futures, thus avoiding losses caused by the increase in transportation costs.

Our research has implications for both policymakers and shipping companies.

For policymakers, the interconnectedness and volatility spillovers between markets present new challenges for regulatory authorities. Given the significant two-way volatility spillovers between crude oil transportation and EU's carbon markets, any single-market regulation could offer a new way to transfer volatility energy across both markets. Therefore, both markets should be incorporated into a unified monitoring and management framework to maintain market stability. Policymakers could mandate 'carbon-adjusted freight agreements' where surcharges are tied to EUA futures, ensuring cost transparency and incentivizing emission reductions. Furthermore, adjusting policies like fuel subsidies or incentivizing new energy technologies in response to crude oil market volatility could mitigate risk transmission and support market sustainability.

For crude oil maritime transportation companies, considering the positive across oil prices and BDTI, along with the status of oil prices as a source of volatility, it is crucial to closely monitor related economic events and assess their impact on crude oil and maritime transportation markets. Timely analysis can help them predict market trends and avoid risks. Specifically, shipping companies should adopt a tiered hedging strategy based on oil price thresholds. For example, when the crude oil price exceeds a certain threshold, a portion of the EUA holdings are allocated to offset freight rate fluctuations, utilizing the negative correlation between crude oil and EU's carbon markets in Phase 4. Additionally, to align with the EU's transition toward greener policies, operators should invest in energy-efficient technologies and explore alternatives to traditional fossil fuels, reducing their reliance on high-carbon vessels.

In future studies, dynamic spillover effects among these three markets will be explored. Analyzing time-varying volatility spillovers will help managers monitor such spillovers in real-time. It benefits policymakers and maritime operators in responding to market volatility. As policies are implemented and markets evolve, examining time-varying volatility spillovers can assess policy impacts and market responses.

Author contributions Ling Sun: Conceptualization; Writing—review and editing; Funding acquisition.

Wen He: Methodology; Formal analysis and investigation; Writing—original draft preparation.

Youshui Lu: Formal analysis and investigation; Supervision.

Wenjing Zhang: Methodology; Writing—original draft preparation.

Zhong Ning: Methodology; Supervision.

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Data availability The source of the data has been mentioned in the manuscript.

Declarations

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