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Interplay Between Green Investment and Market Price Premia in Global Shipping

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ABSTRACT

Existing research emphasises that the driver of green investment is its future profitability. This paper shows that other investors' decisions also influence green investment. We take the example of scrubber installation in shipping, which is optional by regulation but has an established market for trading its underlying asset. It requires an initial capital expenditure but generates increased profitability due to fuel savings and higher freight income. However, the volatility of fuel prices and freight rates renders it challenging for investors to decide on the installation. To examine this dilemma, we develop and estimate a Vector Error Correction Model across the tanker and dry bulk shipping sectors from 2021 to 2024. The results indicate the existence of both short- and long-run cointegrating relationships among the freight rate premium, fuel savings and the size of the scrubber-fitted fleet. A 1% increase in the share of the scrubber-fitted fleet decreases the freight rate premium by 1.4%–3.8% and fuel savings by 0.6%–1.9%. We are the first to provide empirical evidence regarding the peer effect of green investment on market price premia. When undertaking green investments, it is important to consider others' decisions as the potential oversupply of the asset can reduce its future profitability.

1 | Introduction

Traditional asset pricing theory suggests that an investment decision is determined by its future profitability premium. Accordingly, studies related to the clean energy transition emphasise the importance of increased profitability for a green investment. The general assumption is that, within regulation permission, an investor will only undertake a green investment if it is profitable. Numerous financial tools are designed to assess green investments based on future profitability estimation, such as the discounted cash flow model (Oosterom and Hall 2022) and the real option models (Fleten et al. 2016; Flora and Tankov 2025). Furthermore, various studies focus on the unilateral impact of market prices on green investment (Dutta et al. 2020; Duan et al. 2024), or the volatility of market prices (Dutta et al. 2021; Sohag et al. 2023).

Instead, we propose that green investment is also affected by other investors' decisions, as the number of undertakers can alter profitability. The peer effect of investment occurs when an individual's financial decision is influenced by their peers and it is well-justified by economic and finance theories (Bikhchandani et al. 1992; Banerjee 1992). According to the supply and demand theory (Marshall 2013), higher supply of an investment asset leads to reduced profitability.

Although many researchers have tested the validity of peer effect empirically, few have examined it in the context of green investment, and none has done so through understanding the mechanism of market prices. Some researchers support the effectiveness and efficiency of peer effect (Ellison and Fudenberg 1995; Bursztyn et al. 2014), but others find biases and inefficiencies when investors follow their beliefs about other investors (Egan et al. 2014; Schmidt-Engelbertz and Vasudevan 2025). With the example of scrubber installation, this paper empirically tests the validity of the peer effect in influencing market price premia (i.e., income in the form of freight rate premia and costs in the form of fuel price savings) of green investment in shipping.

Studying the peer effect in green shipping investment holds significant implications for both policymakers and firms. Shipping is considered the skeleton of the global economy since it accounts for more than 80% of world trade in terms of volume (Clarksons' SIN 2024). However, it generates around 2.8% of the global greenhouse gas (GHGs) emissions (UNCTAD 2023). Furthermore, NOx and SOx emissions arising from shipping activities account for around 15% of the respective total global emissions, which are harmful to the environment, vegetation and human health (Sathi 2021). The paper examines scrubber installation, a key technology aimed at mitigating SOx that (while not GHGs) are major air pollutants. It is critical to examine scrubber investment, as a timely and smooth green shipping transition is essential for the efficient facilitation of international trade in goods.

In 2005, the International Maritime Organisation (IMO)'s International Convention for the Prevention of Pollution from Ships capped the SOx emissions from marine fuels to 4.5% (IMO 2024). In 2012, the cap was reduced to 3.5% while a further significant reduction of the cap to 0.5% has been implemented from 1 January 2020. Alongside this global cap, a stricter 0.1% cap is in effect in sulphur emission control areas (ECAs) in the Baltic Sea, the North Sea, as well as all seas within 200 nautical miles from the coastline of North America.

The exhaust gas cleaning system (EGS), better known as an SOx-reducing scrubber device or, simply, scrubber, is a technology installed on vessels to scrub the sulphur content from the high sulphur fuel oil (HSFO) as it is burned in the vessel's main engine. Historically, conventional vessels' main engines burnt HSFO, with a sulphur content of typically 3.5%. Since 1 January 2020 though, vessels that are not fitted with a scrubber are obliged to burn very low sulphur fuel oil (VLSFO) to comply with the sulphur cap of 0.5%.

This regulation has introduced a dilemma to shipowners regarding whether to equip their fleet with a scrubber or not. Scrubber installation entails a relatively high capital expenditure. Indicatively, for very large crude oil carriers, this can range from $2.5 to $4.5 million (Drewry 2018). During the installation period, an existing vessel does not earn any operating income for typically one to 2 months (data by Clarksons' SIN 2024). Once installed with a scrubber, the vessel can burn the cheaper HSFO and earn a time-charter (TC) freight premium (i.e., a higher freight rate) compared to the non-scrubber-fitted one.[1] On the other hand, not installing a scrubber allows normal operations without incurring the extra capital expenditure, although the vessel will be burning the more expensive VLSFO—the difference between VLSFO and HSFO is referred to as fuel savings.[2]

Consequently, this investment decision has important financial and commercial implications, as well as may affect fuel and freight prices. Specifically, if the vessel is operated in the spot market, the freight rate received does not depend on whether a scrubber is installed as it is the ship owner and not the charterer who pays for the fuel costs. If the vessel is operated in the TC market though, the freight rate for the scrubber-fitted vessel receives a premium compared to the non-scrubber-fitted one as the charterer reduces their fuel costs by being allowed to burn HSFO instead of VLSFO. As such, one would expect that the TC premium for a scrubber-fitted vessel positively depends on the spread between the VLSFO and HSFO prices.

Shipping economic theory suggests that the TC premium should also depend on the availability of scrubber-fitted vessels. Namely, for a given demand for HSFO-burning fleet, increased supply of scrubber-fitted vessels relative to non-scrubber-fitted ones is expected to decrease the premium paid to charter the former instead of the latter.

As shown in Figure 1, our study explores the interrelationships between green investment and market price premia; more specifically, between scrubber installation, freight rate premium and fuel savings. While most existing studies only focus on how market price premia influence the decision of scrubber installation, supply-and-demand fundamentals suggest that a supply increase of scrubber-fitted vessels is expected to lower the premium paid to charter it. At the same time, the increased supply may also affect the availability of fuels, thereby influencing the fuel savings. What is more, since scrubbers reduce the fuel costs for the charterer of the vessel, one should expect that the freight premium positively depends on the fuel savings.

Due to the following financial charactseristics, scrubber investment is an ideal case for testing the interactions between green shipping investment and market price premia. Scrubber installation is optional for an individual investor by regulation but

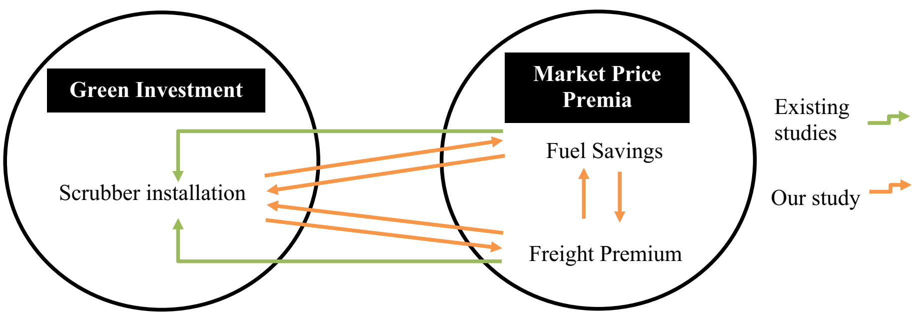

FIGURE 1 | Our contributions to green investment and market price premia. [Colour figure can be viewed at wileyonlinelibrary.com]

has an established market for trading its underlying asset—the scrubber-fitted vessel. The installation requires an initial capital expenditure but generates higher profits by burning fuels that are less expensive and/or producing higher freight income.

Our main research questions are (i) whether financial incentives, in the form of freight and fuel prices, drive the investment decision of scrubber installation; and (ii) whether scrubber investment affects these market price premia in return. The answer to both questions is 'yes'. Our results imply that improved financial performance does drive investment in green technologies. Furthermore, we provide evidence on the peer effect in green investment, suggesting that late adopters may earn less than the expected profitability.

Our paper has both empirical and methodological contributions. From an empirical perspective, we contribute to the literature by providing rigorous data-driven evidence about whether improved financial performance drives an industry's investment in green technologies, and whether peer effect influences green investment decisions. In addition, we contribute by exploring the causal transmission patterns among scrubber-fitted fleet, freight rates and fuel prices at both short- and long-run horizons.

From a methodological point of view, we expand the current literature by introducing a multivariate time series model (VECM), which builds on established shipping economic theory but is adjusted to account for the case of sustainable investments. Installing a scrubber affects the operating cash flows of the vessel throughout its economic life, and we are the first to investigate the dynamic causal linkages between the relative share of scrubber-fitted vessels, their income premia and their fuel savings. We fill in the literature gap by testing and establishing the existence of a common long-run equilibrium among these series and the dynamics of the adjustments towards it.

The rest of the paper is structured as follows. Section 2 is a literature review. Section 3 introduces the data and the empirical framework. Section 4 presents and analyses the results. Finally, Section 5 provides the conclusion.

2 | Literature Review

We aim to fill in three major literature gaps: peer effect in green investment (Section 2.1); the relationships between green investment and market price premia (Section 2.2); and robust econometric assessment of scrubber installation (Section 2.3).

2.1 | Peer Effect in Green Investment

The peer effect theory is based on the psychology of social influence (Cialdini and Goldstein 2004). Peer effect in investment refers to the case where an investor's decision is affected by other investors and it has been developed for decades in behavioural economics (Bikhchandani et al. 1992), and investment theories (Abel 1990; Gali 1994). Peer effect can produce positive or negative results, which has been studied in various topics of finance and economics. However, little is known about peer effect in green investment.

On the one hand, peer effect can bring positive outcomes, which is part of the rationales of 'social learning' (Bandura and Walters 1977) and 'network externality'[3] (Cabral 1990). With respect to 'social learning', peer effect occurs as investors can make improved decisions after obtaining information from previous investors (Bikhchandani et al. 2024). Ellison and Fudenberg (1995) find that, when payoffs can be learnt from a peer's experience, this can result in positive outcomes for the investor. Bursztyn et al. (2014) propose that the rationale for peer effect not only comes from 'social learning' but also 'social utility', in which the utility of possessing an asset is dependent on other investors.

'Network externality' is often related to the diffusion of innovation, where the adoption of new technology or standard positively depends on the number of former adopters. There is abundant literature on this topic, including theoretical economic modelling, behavioural simulation and causal inference. For example, Allen (1982) applies a stochastic theoretical model and finds that the interdependencies among economic agents influence the diffusion of innovation under uncertainty. Xiong et al. (2016) use case study and agent-based simulation methods and find that peer effects happen in the diffusion of innovation through externalities, as well as information and experience sharing. Ouimet and Tate (2020) find empirical evidence that an employee's decision to enter 'employee stock purchase plans' (ESSP) is influenced by their co-workers'. As ESSP is almost always beneficial for employees, the results confirm that peer effect can provide strong positive externalities. Peng et al. (2021) find evidence of positive externalities from the peer effect of firm R&D investment.

On the other hand, peer effect may lead to neutral or negative results, which is related to 'herd behaviour' (Banerjee 1992), 'momentum investment' (Grundy and Martin 2001) and 'second-order belief' (Seo 2009). Numerous studies adopt causal inference approaches with data evidence to prove the ineffectiveness or the shortcomings of peer effect. Kaustia and Rantala (2015) find that firms follow their peers to decide to split their stocks or not, but no clear benefit is shown. Gangopadhyay and Nilakantan (2021) find that Jordanian banks follow their peers in IT investment but do not observe their peers' profitability after the investment. Kaustia and Knüpfer (2012) find that individuals enter the stock market by naively extrapolating positive outcomes from their peers in the neighbourhood areas, and their peers selectively communicate only the positive outcomes. Some studies investigate the biases and inefficiencies caused by 'second-order belief', i.e., when an individual makes decisions based on what they believe others believe. Egan et al. (2014) use a survey method and find that investors' second-order beliefs are inaccurate and biased. Dustan et al. (2022) use an experimental method and find biases from the second-order beliefs about gender performance. Schmidt-Engelbertz and Vasudevan (2025) provide empirical evidence that stock investors' high-order beliefs lead to more speculation and increase market volatility.

On the relevance of green shipping, there are very limited studies that propose or test the idea of peer effect. Wang and Jiao (2022) develop a game theoretical model for two shipping companies, one port and the government in the context of VLSFO adoption, and find that being the leader can bring the shipping company higher profits. Shang et al. (2024) construct a similar economic model, which suggests that a shipping alliance between one port, two shipping companies and the government could promote green investment. However, neither paper has considered peer effect at an aggregate level and could not provide data-driven evidence.

Other research suggests that information spillover exists in green shipping at various levels, such as policymakers, neighbouring countries and the shipping market. Chen et al. (2024) conduct social network analysis on 208 China's green shipping policy documents from 2009 to 2022 and find that policymakers collaborate at various levels to enforce sustainability regulations. Xu et al. (2024) use a spatial model to study 19 EU coastal countries and find that carbon emissions from shipping trade in the EU demonstrate strong correlation and agglomeration. Meng et al. (2023) use wavelet analysis and the spillover index methods on weekly data between 2008 and 2021 and find that there are bidirectional information spillovers between carbon finance markets and the shipping markets. Given that market price premia can be the intermediary of information spillover, we select market price premia to examine peer effect in green shipping.

In a nutshell, our paper expands the literature by examining peer effects on green investment through the mechanism of market price premia. Given the rather slow transition towards net zero and the urgent calls for action from local, national and international authorities, it is both interesting from an academic perspective and of high industry and policy importance to investigate whether and how peer effects affect green initiatives. We have found that peer effects can be beneficial in informing better choices, yet misleading in terms of expected profitability.

2.2 | Green Investment and Market Price Premia

Peer effect can influence green investment, particularly by postponing the decision to invest and wait for others to do so first (Wolske et al. 2020). A popular explanation for the delay is that uncertainty penalises early adopters and therefore delays green investment at a market level. This is supported by the theory of the irreversibility of investment, where uncertainty creates opportunity costs for first movers (Henry 1974; Pindyck 1993; Kogan 2001). Cui and Shibata (2017) suggest that information asymmetry, combined with investment irreversibility, delays investment. Drakos and Tsouknidis (2024) find evidence that uncertainty postpones shipping investment when the level of irreversibility is higher. Davis and Cairns (2017) notice that even partially reversible investment can result in time delay. However, the irreversibility theory cannot fully explain how market price premia influence the timing of green investment. What is more, irreversibility mainly concerns early adopters and does not provide an explanation for late adopters of green investment. Our paper focuses on the interplay between market price premia and a partially reversible green investment, that is scrubber installation. We find that the market can penalise late adopters by reducing their expected profitability.

Our paper sheds light on the optimal timing of green investment under market price premia uncertainty. Uncertainty in green investment includes various aspects such as policy, climate and market prices (Flora and Tankov 2025; Li et al. 2022; Zhao and Luo 2024). Most scholars focus on the adverse impacts of policy uncertainty on green investment (e.g., Kirikkaleli and Adebayo 2024; Sun et al. 2024; Adekoya et al. 2025). Some have explored green investment in the context of market price uncertainty. These studies indicate the linkage between green investment and market price fluctuations, but they do not provide robust causal evidence. For instance, Ghaemi Asl et al. (2025) find that there is multifractal cross correlation between green investment market and crude oil market. Eyraud et al. (2013) find that population and market prices are the determinants of renewable investment.

In the field of shipping finance, a few studies mention that market uncertainty may be a significant factor in influencing investment decisions (Lai et al. 2019; Pouliasis and Bentsos 2024) but have not provided any data-driven evidence on green investment. Other papers argue that market conditions may be the main determinants for green investment in shipping (Metzger 2022; Jia et al. 2024), but they do not identify any direct or indirect linkages between the two. Our study tests the causality between green investment and market price premia in the context of shipping sustainability. We have identified that both early and late adopters can be penalised with inaccurate information about the asset's profitability.

2.3 | Scrubber Installation in Shipping

Most studies assess scrubber installation without considering the impact of the number of undertakers of this green technology on market prices (e.g., Abadie et al. 2017). Table A1 provides a summary of the literature. Our paper fills in the literature gap by providing a robust econometric analysis of scrubber investment and its peer effect on the freight premium and fuel savings.

The existing research focuses on whether scrubber installation is preferred over the use of VLSFO but neglects that market prices and scrubber investment may interact with each other (e.g., Jang et al. 2020). These studies conduct static scenario analysis based on the assumption that the decision of scrubber installation does not influence market prices. They conclude that scrubber installation is preferred under four conditions: when the fuel price differential is high between VLSFO and HSFO; when the remaining economic life of the vessel is long; when the interest rate is low; and when the vessel sails through ECAs frequently (e.g., Panasiuk and Turkina 2015). However, an increase in market price premia may drive up investment, and conversely, an oversupply of scrubber-fitted vessels may reduce the freight premium and fuel savings.

Instead, our study incorporates the fleet supply variable to investigate the multiple Granger (1986) among the fleet supply of scrubber-fitted vessels, fuel savings and freight premium. In turn, this approach allows us to investigate the dynamic relationship between green investment and market uncertainty rather than merely evaluating an investment decision based on (strong) assumptions. No previous study, as far as we are aware, has fully addressed the above.

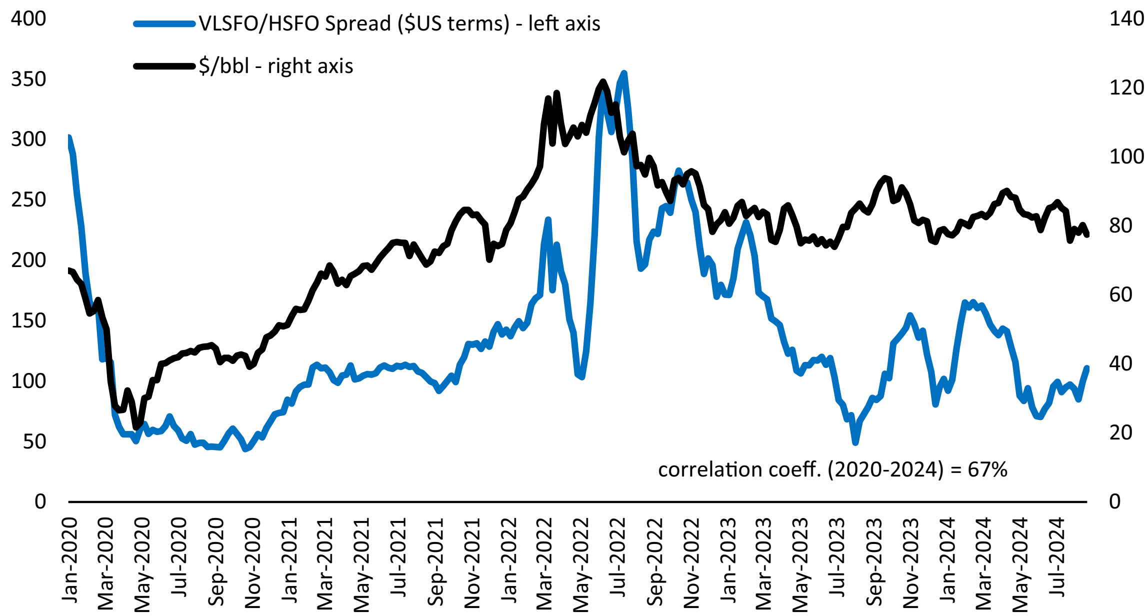

FIGURE 2 | VLSFO/HSFO spread ($ terms) and Brent Crude Oil price ($/bbl, 1-month future contract). *Source:* Data by Clarksons' SIN 2024. [Colour figure can be viewed at wileyonlinelibrary.com]

3 | Data and Methodology

3.1 | Data Description

We collect weekly frequency data from Clarksons' Shipping Intelligence Network (SIN) platform for the period 08/05/2020 to 23/08/2024 on: 1-year TC rates for scrubber-fitted and non-scrubber-fitted vessels in US$/day terms; and prices of HSFO and VLSFO in US$/tonne terms. Furthermore, monthly data from May 2020 to August 2024 are gathered for scrubber-fitted fleet and total fleet development, both in deadweight tonnes (DWT) terms, which is the conventional measure of a vessel's cargo-carrying capacity.[4]

As vessels in different segments or classes are characterised by distinct freight market dynamics, voyage durations, commodity exposure, fuel consumption patterns, etc., our empirical investigation examines major shipping sectors in isolation.[5] The variables used for a given segment differ in terms of whether the vessel has a scrubber installed or not, thus allowing us to focus on the effects of scrubber installation. We focus on each segment, on a global scale, for which there is availability of both TC rates data and the size of the scrubber-fitted fleet, that is VLCC, Suezmax, Aframax, Panamax and Handysize in the tanker market and Capesize (Pacific and Atlantic regions) in the dry bulk market.[6] The complete sample for each segment in the tanker market is 225 observations (08/05/2020 to 23/08/2024) and 195 observations in the dry bulk market (04/12/2020–23/08/2024).

To examine the income premium received by scrubber-fitted over non-scrubber fitted vessels, the $income_{j,t}$ variable is constructed with TC premia (Equation 1).

$$INC_{j,t} = {}^{TC^{SOx}_{j,t}}/_{TC_{j,t}} - 1 \tag{1}$$

where $TC^{SOx}_{j,t}$ and $TC_{j,t}$ are the 1-year TC rates for scrubber-fitted and non-scrubber-fitted eco-vessels respectively, and j denotes the respective market segment. This reflects the operating revenue benefit to the shipowner from installing a scrubber when the vessel is employed in the time-charter market.

We focus on TC rates rather than spot freight rates, as the latter do not depend on whether a scrubber is installed or not as it is the ship owner and not the charterer who pays for the fuel costs. In contrast, TC rates for the scrubber-fitted vessels command a premium over those for non-scrubber-fitted vessels, since the charterer incurs lower fuel costs by being allowed to burn HSFO instead of VLSFO.

While there is no direct benefit in the form of higher freight rates if the scrubber-fitted vessel is employed in the spot market, the shipowner's operating profits still increase due to burning HSFO instead of VLSFO. Specifically, VLSFO is more expensive than HSFO due to its higher level of refinement and the lack of supply capacity amid increasing demand. This price premium is quantified through the $fuel_t$ variable:

$$F_t = {}^{VLSFO_t}/_{HSFO_t} - 1 \tag{2}$$

where the price for each of the two different fuel oil grades, that is $VLSFO_t$ and $HSFO_t$, is estimated as the average fuel cost incurred in the major bunkering ports of Houston, Rotterdam and Singapore.

As it can be observed in Figure 2, the price differential between VLSFO and HSFO has been highly volatile, ranging from roughly $50 to more than $350 over the period 2020–2024. Furthermore, it follows the performance of Brent crude oil prices very closely; for the whole period, the correlation stands at 67% (data by Clarksons' SIN 2024). However, since 2022, the rise of geopolitical risks (war in Ukraine and the resulting sanctions; tensions in the Middle East region) has diverted the oil market from its normal trajectory. Consequently, the relationship between VLSFO/HSFO spread and oil prices seems to have been broken; although still positive, it remains at low levels (Figure 3, data by Clarksons' SIN 2024).

By examining the income and fuel variables, our empirical investigation aims to capture the relative financial performance of scrubber-fitted vessels as well as the demand for such vessels on behalf of charterers. While relevant, the associated capital expenditure (i.e., the cost of scrubber installation) could not be included as a variable in the empirical estimation since no relevant time-series data are available[7]

We also examine whether the composition of the fleet affects the financial performance of scrubber-fitted relative to non-scrubber-fitted vessels, and what determines the scrubber investment decision of shipowners. To that end, we quantify the supply of the scrubber-fitted fleet, $supply_{j,t}$, as a percentage of the overall fleet in that segment, $fleet_{j,t}$; where $fleet^{SOx}_{j,t}$ is the scrubber-fitted fleet:[8]

$$S_{j,t} = {FLT^{SOx}_{j,t}}/{FLT_{j,t}} \tag{3}$$

As Figure 4 suggests, close to the time of the implementation of the new regulation, scrubber installation sharply increased, from 1.3% of the total fleet (in DWT terms) in January 2019 to 11.2% within a year. However, while the share of the scrubber-fitted fleet is continuously increasing, the pace of adoption has slowed down since 2021. As of August 2024, 29.2% and 5.3% of the total fleet in DWT terms and number of vessels, respectively, are scrubber-fitted. In the tanker market, the two figures correspond to 45.7% and 37.6%, while in the dry bulk market to 27.3% and 13.9% (data by Clarksons' SIN 2024). Therefore, there is evidence that less than half of the fleet is scrubber-fitted and, at the same time, there is a tendency for larger vessels to be retrofitted as opposed to smaller ones. The latter implies that scrubbers may be less efficient on smaller size vessels.

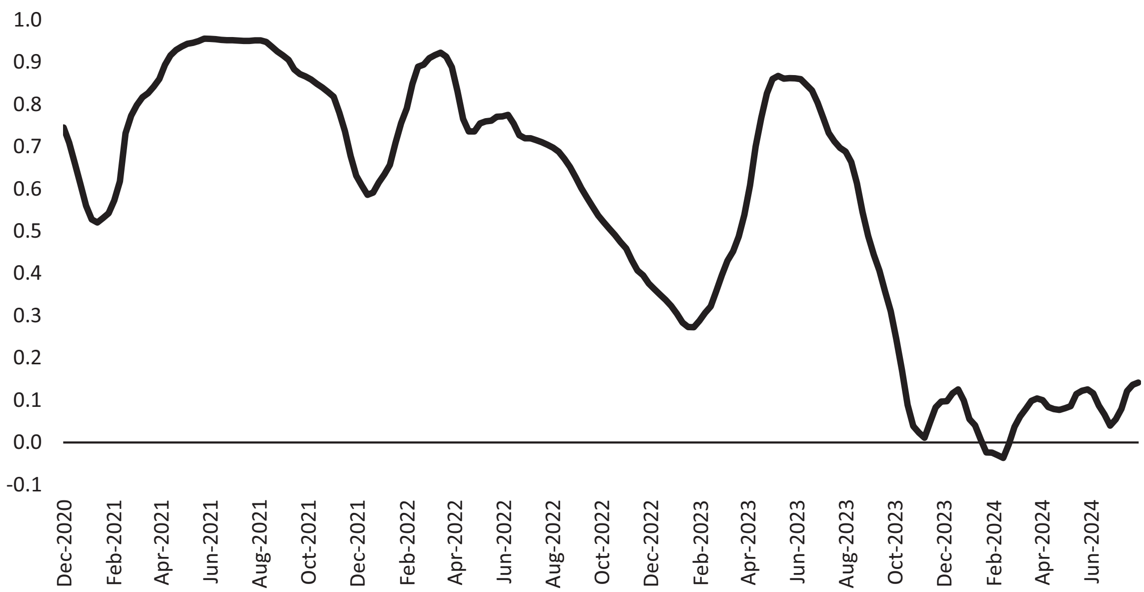

FIGURE 3 | 1-year rolling correlation between VLSFO/HSFO spread and Brent Crude Oil price. *Source:* Data by Clarksons' SIN 2024.

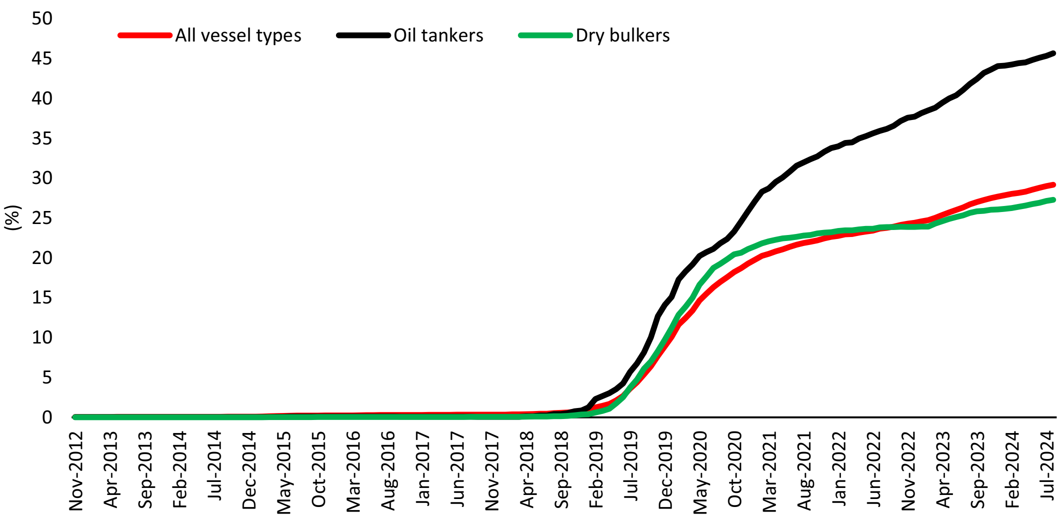

FIGURE 4 | Share of scrubber-fitted vessels as a proportion of the total respective fleet (in DWT terms). *Source:* Data by Clarksons' SIN 2024. [Colour figure can be viewed at wileyonlinelibrary.com]

Oil tanker vessels not only have the highest rate of adoption, but the DWT and number figures are much closer to each other, suggesting that smaller size vessels are also fitting that technology. Finally, as of August 2024, 71.2% of dry bulkers and 69.1% of tankers are retrofitted, indicating that most vessels (in DWT terms) have installed the technology after they were built.

Table 1 summarises the list of variables and their data sources or calculation methods.

TABLE 1 | List of variables.

Variables	Definitions	Data source (or calculation method)
TC^{SOx}	Time-charter rate of scrubber-fitted vessels	Clarksons' SIN
TC	Time-charter rate of non-scrubber-fitted vessels	
$VLSFO$	Fuel price of very low sulphur fuel oil	
$HSFO$	Fuel price of high sulphur fuel oil	
FLT^{SOx}	The number of scrubber-fitted vessels	
FLT	The number of non-scrubber-fitted vessels	
ΔINC	Income premium	$INC_{j,t} = {}^{TC^{SOx}_{j,t}}/{}_{TC_{j,t}} - 1$
ΔF	Fuel saving	$F_t = {}^{VLSFO_t}/{}_{HSFO_t} - 1$
ΔS	Fleet supply	$S_{j,t} = {}^{FLT^{SOx}_{j,t}}/{}_{FLT_{j,t}}$

3.2 | Descriptive Statistics and Diagnostic Tests

Table 2 presents descriptive statistics for the logarithmic returns of the income, fuel and supply variables in the oil tanker and dry bulk markets, and for the different types of vessels. The results suggest that in the tanker market the mean income values for larger size ships are higher than for smaller ones; whereas, for the dry bulk market, the income is negative and larger in the Atlantic region than in the Pacific region. VLCCs, Suezmaxes and Aframaxes exhibit similar unconditional volatilities (standard deviation). However, the pattern breaks for Panamaxes and Handysizes, where the volatility increases, and is highest for the smallest size vessels in the Handysize sector. The fuel variable mean magnitude differs, and its sign alters between the two markets, but this is due to the reduced sample period in the case of the dry bulk market. Regarding supply, we observe no large differences in the mean value for the three larger size vessels (VLCC, Suezmax, Aframax), while it is reduced for the smaller size ones (Panamax, Handysize). The Jarque and Bera (1980) test indicates significant deviations from normal distributions for all variables, and the Ljung and Box (1978) Q statistic for 10th-order autocorrelations reveals that there is serial correlation in all cases.

To assess whether the variables—income, fuel and supply—are non-stationary and to establish their order of integration, we

TABLE 2 | Descriptive statistics.

	$\bar{x}$	SD	$\hat{\alpha}^3$	$\hat{\alpha}^4$	JB	p	$Q(10)$	p	Obs.
ΔINC_{vlcc}	0.0033	0.0741	−0.53	14.93	1339.28	0.00	523.50	0.00	224
ΔS_{vlcc}	0.0036	0.0034	1.68	5.56	164.99	0.00	615.34	0.00	221
$\Delta INC_{suezmax}$	0.0018	0.0653	2.07	25.75	4990.97	0.00	584.33	0.00	224
$\Delta S_{suezmax}$	0.0032	0.0036	2.39	11.15	822.62	0.00	628.10	0.00	221
$\Delta INC_{aframax}$	0.0017	0.0506	2.14	19.72	2780.33	0.00	567.33	0.00	224
$\Delta S_{aframax}$	0.0033	0.0030	1.41	4.63	97.86	0.00	632.41	0.00	221
$\Delta INC_{panamax}$	0.0011	0.0701	4.19	52.26	23,304.47	0.00	712.40	0.00	224
$\Delta S_{panamax}$	0.0026	0.0040	1.17	3.00	50.84	0.00	621.30	0.00	221
$\Delta INC_{handysize}$	−0.0009	0.0956	1.38	54.73	25,051.88	0.00	561.77	0.00	224
$\Delta S_{handysize}$	0.0022	0.0027	1.74	5.43	165.25	0.00	661.45	0.00	221
ΔF_{tanker}	−0.0022	0.1131	−0.13	4.72	28.19	0.00	872.33	0.00	224
$\Delta INC^{atlantic}_{capesize}$	−0.0025	0.1377	−1.32	41.70	12,165.35	0.00	934.24	0.00	194
$\Delta INC^{pacific}_{capesize}$	−0.0009	0.1862	−0.44	26.95	4641.63	0.00	933.21	0.00	194
$\Delta S_{capesize}$	0.0009	0.0010	0.82	2.95	21.59	0.00	863.20	0.00	192
$\Delta F_{drybulk}$	0.0005	0.1146	−0.14	5.00	33.02	0.00	1092.10	0.00	194

Note: The sample period is 08/05/2024 to 23/08/2024 for the tanker market, and 04/12/2020 to 23/09/2024 for the dry bulk market. $\bar{x}$ denotes the mean, SD the standard deviation and $\hat{\alpha}^3$ and $\hat{\alpha}^4$ the skewness and kurtosis, respectively. JB is the Jarque and Bera (1980) $\chi^2(2)$ distributed test statistic for normality. $Q(10)$ is the Ljung and Box (1978) Q statistic that measures the autocorrelation of order 10 in the raw series, assuming a distribution of $\chi^2(10)$.

TABLE 3 | Unit root tests.

	PP	*KPSS*	ADF(μ)	ADF(τ)	*GHP*	*ADF(μ) CI*	*ADF(τ) CI*	*P*
INC_{vlcc}	−0.339 (0.9861)	1.9832	−2.317 (0.1465)	−2.128 (0.5267)	0.937 (0.362)	[0.89, 1.03]	[0.92, 1.04]	−4.460 (0.134)
S_{vlcc}	−0.302 (0.9962)	1.8877	−2.422 (0.1366)	−2.9426 (0.1152)	0.897 (0.286)	[0.87, 1.03]	[0.89, 1.03]	−4.88 (0.128)
$INC_{suezmax}$	−0.266 (0.7487)	1.8230	−2.128 (0.2238)	−3.062 (0.1135)	0.834 (0.256)	[0.84, 1.02]	[0.78, 1.03]	−4.39 (0.142)
$S_{suezmax}$	−0.800 (0.8378)	1.9601	−2.844 (0.1180)	−2.887 (0.1947)	0.894 (0.384)	[0.89, 1.03]	[0.98, 1.05]	−4.59 (0.137)
$INC_{aframax}$	−1.894 (0.0761)	0.9643	−3.022 (0.0923)	−3.088 (0.1156)	1.072 (0.397)	[0.92, 1.01]	[0.88, 1.03]	−4.33 (0.145)
$S_{aframax}$	−0.295 (0.6648)	0.9451	−2.725 (0.0851)	−2.437 (0.344)	0.904 (0.288)	[0.98, 1.04]	[0.89, 1.04]	−4.07 (0.875)
$INC_{panamax}$	−0.921 (0.9837)	1.7501	−3.074 (0.1136)	−3.512 (0.345)	0.937 (0.362)	[0.95, 1.04]	[0.94, 1.04]	−4.52 (0.186)
$S_{panamax}$	−0.340 (0.8432)	1.0572	−1.051 (0.7345)	−2.672 (0.256)	0.899 (0.316)	[0.96, 1.03]	[0.98, 1.05]	−4.36 (0.144)
$INC_{handysize}$	−0.308 (0.9432)	1.9081	−1.134 (0.5642)	−2.851 (0.234)	0.834 (0.256)	[0.99, 1.02]	[0.89, 1.04]	−4.45 (0.138)
$S_{handysize}$	−0.273 (0.9532)	0.8752	−2.452 (0.1288)	−2.363 (0.3978)	0.905 (0.287)	[0.91, 1.04]	[0.87, 1.03]	−4.57 (0.167)
F_{tanker}	−0.385 (0.9765)	1.0326	−1.323 (0.5632)	−3.062 (0.1881)	0.902 (0.290)	[0.91, 1.04]	[0.89, 1.04]	−4.02 (0.102)
$INC_{capesize}^{atlantic}$	−0.222 (0.8245)	0.8864	−1.127 (0.6573)	−2.387 (0.1135)	0.908 (0.280)	[0.99, 1.04]	[0.80, 1.03]	−4.43 (0.115)
$INC_{capesize}^{pacific}$	−0.283 (0.8711)	0.9523	−1.265 (0.4871)	−2.567 (0.1167)	0.834 (0.256)	[0.95, 1.03]	[0.89, 1.03]	−4.58 (0.135)
$S_{capesize}$	−0.317 (0.9053)	1.0531	−2.346 (0.4673)	−3.102 (0.1682)	0.905 (0.256)	[0.98, 1.03]	[0.97, 1.05]	−4.24 (0.128)
$F_{drybulk}$	−0.330 (0.9218)	1.3765	−2.341 (0.2043)	−2.557 (0.2552)	0.904 (0.288)	[0.99, 1.04]	[0.95, 1.03]	−4.56 (0.122)

Note: The table presents all unit root tests for the series in levels. PP refers to the Phillips (1988) test with intercept and trend; MacKinnon (1996) one-sided *p* values are displayed in brackets. KPSS is the Kwaitkowski et al. (1992) test with intercept and trend; the 1% and 5% critical values are 0.739 and 0.463, respectively. ADF(μ) and ADF(τ) are the Augmented Dickey and Fuller (1981) tests, respectively, with intercept and trend, MacKinnon (1996) one-sided *p* values are reported in brackets. Lag length selection is based on the minimisation of the Schwarz Bayesian Information Criterion (SBIC) in the test equation for all tests. The 90% CIs are estimated using Stock (1991) method for the largest autoregressive root. GPH is the Geweke and Porter-Hudak (1983) estimate of the integration order; standard errors are reported in parentheses. *P*, in the last column, reports the Perron (1997) test for a unit root under a structural break in trend and intercept; *p* values are reported in brackets. No evidence of a break is found.

conduct several assessments considering the limitations of classical unit root tests (Table 3). Namely, the Augmented Dickey and Fuller (1979), the Phillips (1988) and the Kwaitkowski et al. (1992) tests. Given the low power of unit-root tests in small samples, which may imply difficulties in distinguishing between the presence of a unit root and stationarity (Christiano and Eichenbaum 1990; Rudebusch 1993), we ensure robustness of our conclusions and quantify the unit root persistence by deriving the 90% confidence intervals (CIs) for the most significant unit root (Stock 1991).

The CIs reported in Table 3 assess the persistence of the unit root, suggesting that it is rather persistent as all lower bounds are above 0.80[9] for both the ADF intercept only (ADF(μ)) and the ADF trend and intercept (ADF(τ)) tests. Furthermore, the Geweke and Porter-Hudak (1983) method examines fractional integration, suggesting that most estimates of the memory parameter d fall significantly in the neighbourhood of one. Finally, we conduct the Perron (1997) unit root test to allow the evaluation of the null hypothesis of integration under the presence of structural breaks.

To establish that our series are not integrated of higher-than-one order, the tests are repeated using first differences as well. Results from the tests, in Table 3, indicate non-stationarity of all series in level terms, with stationarity in their first differences, thus integrated of order one, $I(1)$.

Since the series are all $I(1)$, we examine the existence of cointegration to verify a long-run relationship among them. Table 4 exhibits the evidence of the Johansen and Juselius (1990; 1993) test for cointegration. This approach overcomes the well-known limitations of the Johansen (1988, 1991) approach in small samples and offers the further advantage of allowing non-normal and conditional heteroskedastic innovations (Gonzalo 1994; Cheung and Lai 1993); hence, it is more appropriate for our dataset. The results from the trace and maximal eigenvalue tests, reported in Table 4, indicate the existence of at most a single cointegrating vector or two common stochastic trends in all segments at 5% significance level. The lag length is decided according to the Schwarz Bayesian Information Criterion (SBIC) (Schwarz 1978). The results are invariant to minor modifications of the lag length, supporting the existence of a single cointegrating vector. Since the Maximum Likelihood estimator may be biased in small samples, estimation of the testing equations is also performed with the dynamic ordinary least squares (DOLS) of Stock and Watson (1993).[10] The two sets of estimates are very similar, confirming robustness of our conclusions.

Normalising the income coefficient in the cointegrating equation, the levels of significance suggest that each of these restrictions is rejected for all segments at the 99% significance level. This suggests that all variables in the cointegrating vector are statistically significant and adjust accordingly to eliminate any short-run disequilibrium.

TABLE 4 | Cointegration test results.

Segments	Lags	Hypothesis		Test statistics	
		H_0	H_A	λ_{max}	λ_{trace}
VLCC	1	$r=0$	$r\geq 0$	68.36[b]	215.64[b]
		$r\leq 1$	$r>1$	43.78	147.32
		$r\leq 2$	$r>2$	23.45	70.43
Suezmax	1	$r=0$	$r\geq 0$	75.33[b]	206.84[b]
		$r\leq 1$	$r>1$	40.20	120.45
		$r\leq 2$	$r>2$	21.33	69.33
Aframax	1	$r=0$	$r\geq 0$	65.54[b]	243.56[b]
		$r\leq 1$	$r>1$	34.21	121.83
		$r\leq 2$	$r>2$	22.12	65.42
Panamax	1	$r=0$	$r\geq 0$	83.21 [b]	217.62[b]
		$r\leq 1$	$r>1$	40.01	109.65
		$r\leq 2$	$r>2$	21.76	66.32
Handysize	1	$r=0$	$r\geq 0$	79.08 [b]	211.56 [b]
		$r\leq 1$	$r>1$	42.65	109.02
		$r\leq 2$	$r>2$	25.34	60.45
Capesize (A)	1	$r=0$	$r\geq 0$	65.03 [b]	66.75 [b]
		$r\leq 1$	$r>1$	40.03	98.33
		$r\leq 2$	$r>2$	36.55	60.45
Capesize (P)	1	$r=0$	$r\geq 0$	65.03 [b]	66.75 [b]
		$r\leq 1$	$r>1$	38.50	40.01
		$r\leq 2$	$r>2$	19.04	22.03

Note: The table presents the estimates based on the Johansen and Juselius (1990, 1992) test for cointegration. The lag length is chosen according to the SBIC information criterion (Schwarz 1978). a, b and c represent the significance levels of 1%, 5% and 10%, respectively.

3.3 | Vector Error Correction Model

In presence of cointegration, a VECM can be specified to identify the nature of the long- and short- run relationships among the variables of interest. Using a model based on the difference variables only may imply loss of information on linkages present solely in the long run, which may prove to be useful for shipowners, charterers and policy makers alike. In the presence of a cointegrating relationship, there always exists a corresponding error-correction representation (Engle and Granger 1987) that captures the disequilibrium level in the long run due to changes in the dependent and other independent variables.

The model equations are defined as follows:

$$\Delta INC_{j,t}=\alpha_{01}+\sum_{i=1}^{q}\alpha_{1,i}\Delta INC_{j,t-i}+\sum_{i=1}^{q}\beta_{1,i}\Delta F_{t-i}+\sum_{i=1}^{q}\delta_{1,i}\Delta S_{j,t-i} +\gamma_1\left(INC_{j,t-i}+\theta_1 F_{t-i}+\theta_2 S_{j,t-i}+\theta_{01}+\theta_{02}\right)+\varepsilon_{1,t} \tag{4}$$

$$\Delta F_t=\alpha_{02}+\sum_{i=1}^{q}\alpha_{2,i}\Delta INC_{j,t-i}+\sum_{i=1}^{q}\beta_{2,i}\Delta F_{t-i}+\sum_{i=1}^{q}\delta_{2,i}\Delta S_{j,t-i} +\gamma_2\left(INC_{j,t-i}+\theta_1 F_{t-i}+\theta_2 S_{j,t-i}+\theta_{01}+\theta_{02}\right)+\varepsilon_{1,t} \tag{5}$$

$$\Delta S_{j,t}=\alpha_{03}+\sum_{i=1}^{q}\alpha_{3,i}\Delta INC_{j,t-i}+\sum_{i=1}^{q}\beta_{3,i}\Delta F_{t-i}+\sum_{i=1}^{q}\delta_{3,i}\Delta S_{j,t-i} +\gamma_3\left(INC_{j,t-i}+\theta_1 F_{t-i}+\theta_2 S_{j,t-i}+\theta_{01}+\theta_{02}\right)+\varepsilon_{1,t} \tag{6}$$

The short-run relationships are quantified by the slope coefficients of the differenced variables and the terms in brackets. For the income and fuel variables, q is equal to one, indicating that the time lag is one week; for the supply variable, the time lag is set as four weeks. The longer time lag in the supply variable accounts for the time delay in vessel purchase, as it takes more time to observe changes in fleet supply. $\left(INC_{j,t-i}+\theta_1 F_{t-i}+\theta_2 S_{j,t-i}+\theta_{01}+\theta_{02}\right)$ is the error correction term (ECT) which represents the cointegrating (long-run) relationship between the series. The parameter γ_i measures the adjustment speed of the series towards the long-run equilibrium. The model allows inference on both short- and, up to a degree, long- run linkages. Specifically, VECM enables testing for Granger causality among variables. The most popular test of Granger causality in cointegrated vector autoregression (VAR) with I(1) variables is the Johansen (1988, 1991) test. The test is robust to some extent to the existence of non-normality and heteroskedasticity (Cheung and Lai 1993), even if it suffers from small sample bias (Toda and Yamamoto 1995). We have also performed simple Granger causality tests (provided in Table A2) which reveal reverse causality exists for all variables. The only exceptions are causality running from (a) income premia to supply in the Aframax segment, (b) from fuel savings to income premia and supply in the Aframax segment, and finally, (c) from supply in the Aframax segment to fuel savings.

4 | Results and Discussion

The estimation results in Tables 5 and 6 suggest that the model can capture a large fraction of the variation in the income, fuel and supply variables since all adjusted R-squared values are above 80%, with most approaching 90%. Furthermore, all gamma coefficients (Column $\gamma = 1, 2, 3$) are small in magnitude and statistically significant, indicating an adequate specification of the VECM model. Their negative signs imply that, if a positive (negative) deviation from the long-run equilibrium is present, the respective variable(s) will decrease (increase) to revert to it. For example, the income premium is expected to decrease following an increase in the previous period.

In each segment, both freight premium (income) and fuel savings are strongly associated with the supply of the scrubber-fitted fleet 4 weeks later (Equation 6; Column $\Delta supply_{j,t}$). As the income from scrubber-fitted vessels increases compared to non-scrubber-fitted ones', it becomes more financially attractive to instal a scrubber. This is also the case when the VLSFO price rises relative to the HSFO one, for two reasons. If the shipowner operates the vessel in the spot market, their fuel costs substantially decrease by burning HSFO instead of VLSFO. If instead the vessel is leased out in a TC contract, while the shipowner does not incur the fuel cost, the scrubber option becomes more attractive to potential charterers as it largely reduces their fuel costs. Note that the magnitude and significance of the three coefficients is much smaller in the supply equation compared to the income and fuel ones. In general, a 1% increase in the TC premium results in a 0.0002% to 0.0057% rise in the future scrubber-fitted fleet size, ceteris paribus; a 1% increase in the fuel spread, in a 0.0003% to 0.0033% rise in the future scrubber-fitted fleet size, ceteris paribus; and a 1% increase in the supply, in a 0.0012% to 0.0045% decrease in the future scrubber-fitted fleet, ceteris paribus. This is because, on the one hand, a long-term decision as the installation of a scrubber, does not only depend on the fuel and TC conditions at one point in time and, on the other hand, an for example 0.003% change in the fleet composition is rather large in magnitude.

As discussed in Section 1, scrubbers have certain limitations that may deter vessel owners from equipping their vessels with one: the associated capital and operating expenditure; the off-hire period during the retrofit; and challenges regarding the installation process and the scrubber operation per se. Panasiuk et al. (2018) suggest that the scrubber installation impacts a vessel's stability, deadweight, trim, heel and keel. Thus, its exact location of installation on a vessel is crucial to optimise its efficiency and effectiveness. Therefore, it is essential to examine the variables that influence shipowners' decision to instal a scrubber. Note that, since installing a scrubber takes considerable time, the fourth lag of the right-hand-side variables is incorporated in Equation (6)—instead of the first lag, which is the case in Equations (4) and (5). The results remain valid even when the specifications have different lags.

Moreover, the supply of scrubber-fitted vessels negatively affects the size of the respective fleet four weeks later. A 1% increase in the supply results in a 0.0012% to 0.0045% decrease in the future scrubber-fitted fleet, ceteris paribus. As more vessels become equipped with a scrubber, shipowners might be less willing to install scrubbers, perceiving that there is less residual demand for scrubber-fitted vessels from the charterers and that the lower availability of HSFO can lead to a price increase of the fuel. The coefficient of the income variable is much smaller in magnitude, ranging from 0.0% to 0.3%, suggesting that movements in the fuel and supply variables have much stronger impacts on income compared to its past values. These findings can inform companies' chartering policies while ship brokers can incorporate that information in their assessments of the future TC rates and advise their clients accordingly.

Practitioners and policymakers alike have raised concerns regarding the current and future price differential between VLSFO and HSFO and whether there will be sufficient supply of both fuels in the future to accommodate the needs of the maritime industry. On the one hand, there is the view that HSFO, being the conventional and less refined fuel, will remain available for vessel bunkering. The opposing view is that, with the increasing need for VLSFO, the spread between the two will gradually diminish. Therefore, VLSFO will become the conventional fuel oil, and major ports will only supply this in the future. For the time being, all major bunkering locations, including Singapore, Rotterdam, Gibraltar, Fujairah, supply both fuels. However, if the supply of HSFO is reduced in the future, scrubber-fitted vessels will have to pre-order their bunkers or deviate from their route for bunkering purposes. This may eventually reduce profitability and create disputes between owners and charterers.

The results from Equation (5) (Column $\Delta F_{j,t}$) help shed light on that question. Namely, if the share of the scrubber-fitted fleet increases by 1%, the industry can expect a significant decrease in the fuel spread, ranging from 0.6% to 1.9%, other things equal. This is due to an increasing number of such vessels that are associated with higher demand for HSFO relative to VLSFO, which ceteris paribus, results in a narrower fuel spread. The supply of the scrubber-fitted fleet is also significantly related to next week's income premium (Equation 4, Column $\Delta INC_{j,t}$). If the scrubber-fitted fleet has increased by 1%, the income premium is expected to roughly decrease by 1.4% to 3.8% in the subsequent period, other things equal. The reason for the income premium decline is that the higher supply of scrubber-fitted vessels over-accommodates the charterers' need for such vessels.

Interestingly, while the signs and significance of the fuel and supply coefficients in the long run (i.e., θ_1 and θ_2) are consistent with the ones in the short run, the magnitudes differ. On one side, the installation of a scrubber is a long-term investment decision that affects the aggregate fleet and not only the specific retrofitted vessel. Therefore, scrubbed installation has a much stronger effect on the income premium in the long run. On the other side, fluctuations in the fuel spread significantly affect the income premium in the short run, as it determines the charterers' costs; hence, the effect of fuel spread diminishes in the long run. This aligns with the apparent volatile nature of the fuel variable (Figure 2).

Last but not least, the income premium and fuel savings influence each other. A 1% increase in the income premium results in a 0.06% to 0.99% increase in the fuel savings in the next week, ceteris paribus. Namely, when the freight premium required to charter a scrubber-fitted vessel has increased, charterers become keener to adopt non-scrubber-fitted vessels, which drives the price of HSFO up. A 1% increase in fuel savings results in a 0.4% to 1.6% increase in the income premium, ceteris paribus. The explanation is along

TABLE 5 | Results of VECM (Tanker market).

$$\Delta INC_{j,t} = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_1 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \tag{Eq. 4}$$

$$\Delta F_t = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_2 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \tag{Eq. 5}$$

$$\Delta S_{j,t} = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_3 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \tag{Eq. 6}$$

	Estimated Model					Cointegrating equation				
	$\gamma = 1, 2, 3$	$\Delta INC_{j,t}$	ΔF_t	$\Delta S_{j,t}$	$\overline{R}^2$	1	θ_1	θ_2	θ_{01}	θ_{02}
$j =$ VLCC					0.896	1	0.0658[a] (0.000)	−2.3278[a] (0.001)	−0.0058	1.7496
$\Delta INC_{j,t-1}$	−0.0012[a] (0.000)	0.0234[c] (0.061)	0.9918[b] (0.038)	0.0010[c] (0.055)						
ΔF_{t-1}	−0.0051[b] (0.031)	0.8516[a] (0.007)	0.3507[c] (0.087)	0.0003[b] (0.028)						
$\Delta S_{j,t-4}$	−0.0019[a] (0.003)	−2.0348[a] (0.008)	−1.0683[b] (0.034)	- 0.0028[c] (0.076)						
$j =$ Suezmax					0.873	1	0.0593[a](0.005)	−3.8787[a] (0.001)	−0.0016	0.6685
$\Delta INC_{j,t-1}$	−0.0075[a] (0.005)	0.0359[b] (0.007)	0.9566[b] (0.030)	0.0057[b] (0.035)						
ΔF_{t-1}	−0.0603[b] (0.035)	0.7019[c] (0.061)	0.3560[a] (0.008)	0.0006[b] (0.041)						
$\Delta S_{j,t-4}$	−0.0012[a] (0.005)	−3.8062[a] (0.007)	−1.8846[a] (0.001)	−0.0039[c] (0.068)						
$j =$ Aframax					0.810	1	0.0604[c] (0.052)	- 5.1945[c] (0.076)	−0.0006	0.1194
$\Delta INC_{j,t-1}$	−0.0043[a] (0.006)	0.1365[c] (0.067)	0.2156[c] (0.074)	0.0002[c] (0.074)						
ΔF_{t-1}	−0.0073[b] (0.045)	0.3920[a] (0.007)	0.3735[b] (0.041)	0.0023[b] (0.021)						
$\Delta S_{j,t-4}$	−0.0010[c] (0.071)	−2.4557[a] (0.003)	−0.9782[b] (0.050)	−0.0032[a] (0.063)						
$j =$ Panamax					0.894	1	0.0319[a] (0.001)	−2.7158[a] (0.008)	−0.0007	0.0793
$\Delta INC_{j,t-1}$	−0.0061[a] (0.004)	0.0241[c] (0.057)	0.3672[b] (0.045)	0.0002[b] (0.030)						
ΔF_{t-1}	−0.0092[b] (0.03)	0.9211[b] (0.033)	0.3507[a] (0.009)	0.0003[b] (0.046)						
$\Delta S_{j,t-4}$	−0.0095[a] (0.005)	−1.4419[a] (0.007)	−0.9272[b] (0.037)	−0.0012[c] (0.076)						

(Continues)

TABLE 5 | (Continued)

j = Handysize					0.889	1	0.0014[a]	−4.6173[a]	−0.0018	1.2819
							(0.008)	(0.000)		
$\Delta INC_{j,t-1}$	−0.0072[a]	0.0337[c]	0.7389[c]	0.0002[c]						
	(0.009)	(0.071)	(0.076)	(0.054)						
ΔF_{t-1}	−0.0058[a]	0.9948[b]	0.3730[c]	0.0003[b]						
	(0.001)	(0.031)	(0.075)	(0.035)						
$\Delta S_{j,t-4}$	−0.0064[b]	−2.5148[a]	−1.0034[c]	−0.0016[c]						
	(0.015)	(0.001)	(0.062)	(0.073)						

Note: Superscripts a, b, and c indicate significance levels of the 1%, 5% and 10%, correspondingly. Values in (.) are standard errors.

the same lines, that is when it is much more expensive to burn VLSFO compared to HSFO, charterers are willing to pay relatively more to lease a scrubber-fitted vessel since it will substantially reduce their fuel costs.

Post estimation diagnostic tests confirm lack of serial correlation and heteroskedasticity in the model residuals. To examine whether a one-time structural break occurred in the cointegration space, we test for structural stability using a SupF test for I(1) processes proposed by Hansen (1992). The null hypothesis is that there is no structural change, whereas the alternative hypothesis is that there is a sharp or sudden shift in regime that occurred at an unknown point in time. The Hansen (1992) test for stability of the cointegrating relationship confirms that our parameters are stable since p values of the supF test are above 0.05.

These results have significant implications not only for the industry but also for policymakers. The documented bidirectional relationship between the supply of green assets and their market price premia suggests that investors shall evaluate a green investment based on both the projected future income and the decisions of competitors (peer effect). Specifically, the decision to invest in green initiatives is influenced by the expected future income, which in turn, is affected by the number of first movers undertaking green investments.

We pioneer in providing empirical evidence suggesting that peer effect exists in green investment through the mechanism of market price premia. A number of existing studies find that policy and market price uncertainties affect green investment (Li et al. 2022; Sun et al. 2024; Zhao and Luo 2024), while green investment in shipping is driven by financial incentives (Baştuğ et al. 2024; Moutzouris et al. 2024; Shang et al. 2024; Xuan et al. 2024). Adding to these findings, this paper demonstrates that an increase in green investment can negatively impact its future profitability. Our results document the effectiveness of peer effect, that is that an investor makes improved decisions when updating their information through observing others' investment decisions (Ellison and Fudenberg 1995; Bursztyn et al. 2014; Wang and Jiao 2022).

This study also contributes to the discussion about the timing of green investment. Previous studies emphasise that the delay in green investment is due to its irreversibility, which creates an opportunity cost (Flora and Tankov 2025; Wolske et al. 2020). We find that such delay may be attributed to market participants waiting to observe the profitability realised by their peers before investing, as early adopters have inadequate information about the profitability of a green investment. Despite this informational advantage, our findings indicate that late undertakers may experience lower profitability (subject to the capital cost of the green technology not significantly decreasing over time) due to the subsequent oversupply of the green asset. This is in line with the documented inefficiency and biases related to peer effect (Egan et al. 2014; Schmidt-Engelbertz and Vasudevan 2025), where following others may not result in the desired outcome.

From a policy and regulatory point of view, our findings indicate that the interplay between market price premia and green investment may penalise both the early adopters and the late undertakers. Policymakers that aim to facilitate the sustainability transition shall prioritise motivating early adoption so that peer effect is formed which, in turn, could mobilise more risk averse investors to follow. Early adoption can be encouraged by clearly demonstrating its potential financial benefits and designing supportive instruments, such as feed-in tariffs (Couture and Gagnon 2010) and green bonds (Bhutta et al. 2022).

5 | Conclusion

A smooth green transition in shipping ensures the well-functioning of the industry and the efficient facilitation of world trade. This paper selects scrubber installation to assess the relationship between green investment and market price premia in shipping. Since January 2020, when the IMO's 0.5% sulphur cap took effect, vessel owners have faced the dilemma of either incurring the capital expenditure to fit a scrubber system or switching to a more expensive fuel.

Various studies have evaluated scrubber installation from an investment appraisal perspective; however, as far as we are aware, this paper is the first to employ data-driven empirical analysis to examine the dynamic interactions between fuel prices, freight rates and the green composition of the fleet. The results from our Vector Error Correction Model suggest that both short- and long-run cointegrating relationships exist among the fuel savings, the income premium and the size of the scrubber-fitted fleet.

Using weekly data across various oil tanker and dry bulk segments from 2021 to 2024, we find that a 1% increase in either the income premium or the fuel savings results in a 0.0002%–0.0057% rise in the scrubber-fitted fleet size. Conversely, a 1% increase in the

TABLE 6 | Results of VECM (Dry Bulk market).

$$\Delta INC_{j,t} = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_1 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \quad \text{(Eq. 4)}$$

$$\Delta F_{t} = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_2 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \quad \text{(Eq. 5)}$$

$$\Delta S_{j,t} = \sum_{i=1}^{q} a_i \Delta INC_{j,t-i} + \sum_{i=1}^{q} a_i \Delta F_{t-i} + \sum_{i=1}^{q} a_i \Delta S_{j,t-i} + \gamma_3 \left(INC_{j,t-i} + \theta_1 F_{t-i} + \theta_2 S_{j,t-i} + \theta_{01} + \theta_{02} \right) + \varepsilon_{1,t} \quad \text{(Eq. 6)}$$

	Estimated Model					Cointegrating equation				
	$\gamma = 1, 2, 3$	$\Delta income_{j,t}$	$\Delta fuel_{j,t}$	$\Delta supply_{j,t}$	$\overline{R}^2$	1	θ_1	θ_2	θ_{01}	θ_{02}
j = Capesize (Atlantic)					0.893	1	0.8762[b]	−3.7820[b]	−0.0020	0.4584
							(0.042)	(0.039)		
$\Delta INC_{j,t-1}$	−0.0386[a]	0.0752[c]	0.0567[c]	0.0052[c]						
	(0.005)	(0.078)	(0.090)	(0.065)						
ΔF_{t-1}	−0.0052[b]	1.6048[a]	0.2482[c]	0.0033[c]						
	(0.011)	(0.006)	(0.068)	(0.070)						
$\Delta S_{j,t-4}$	−0.0043[a]	−2.6530[a]	−0.5630[c]	−0.0022[c]						
	(0.003)	(0.005)	(0.078)	(0.081)						
j = Capesize (Pacific)					0.882	1	0.6791[a]	−3.9716[a]	−0.0059	0.7893
							(0.001)	(0.001)		
$\Delta INC_{j,t-1}$	−0.0043[a]	0.3125[c]	0.0630[c]	0.0014[c]						
	(0.000)	(0.083)	(0.065)	(0.080)						
ΔF_{t-1}	−0.0004[a]	1.1772[b]	0.1870[c]	0.0027[c]						
	(0.008)	(0.038)	(0.052)	(0.065)						
$\Delta S_{j,t-4}$	−0.0071[a]	−2.5910[a]	−0.6920[b]	−0.0045[c]						
	(0.009)	(0.007)	(0.040)	(0.085)						

Note: Superscripts a, b, and c indicate significance levels of 1%, 5% and 10%, correspondingly. Values in (.) are standard errors.

share of the scrubber-fitted fleet decreases the income premium by 1.4%–3.8% and the fuel savings by 0.6%–1.9%. Our findings suggest that the supply of scrubber-fitted vessels is determined by its future profitability (income premium and fuel savings), but a higher supply of scrubber-fitted vessels reduces future profitability.

We are the first to document the peer effect in green investment through market price premia. Changes in the adoption of green technologies at an industry level can impact the future profitability of such investments. These findings demonstrate that both profitability and peers' decisions are important when undertaking green investment decisions. Additionally, our results indicate that early adopters of green technologies may suffer from insufficient information about their profitability, while late undertakers could experience lower-than-expected profitability.

Our paper has profound implications for practitioners and policymakers. Investors need to base their decisions not only on historical income but also on their peers' decisions. Policymakers shall focus on encouraging early adopters when advocating for the sustainability transition. Early adopters can trigger peer effects and encourage widespread, industry-level green investment. To encourage early participants, there needs to be more clarity on the forthcoming financial benefits.

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Data Availability Statement

The data that support the findings of this study are available from Clarksons Shipping Intelligence Network. Restrictions apply to the availability of these data, which were used under licence for this study. Data are available from https://www.clarksons.net with the permission of Clarksons Shipping Intelligence Network.

Endnotes

[1] Time-charter is a type of contract where the vessel is leased to a charterer for a period that typically ranges from 6 months to 5 years. The shipowner earns a pre-agreed fixed income per day, while the charterer bears the vessel's fuel costs.

[2] A third option is to adopt another compliant fuel like liquefied natural gas (LNG) or methanol, instead of fuel oil. This solution requires an entirely new engine room and propulsion mechanism and is viable only on new vessels as it does not make any economic sense for an existing vessel to switch to alternative fuels (apart from biofuels). Furthermore, the decision to incorporate such alternative fuels is primarily associated with the reduction of GHGs rather than SOx. While, in the coming decades, the use of alternative fuels will result in decreased SOx emissions, most vessels and especially the dry bulk and tanker ones (which are the focus of this paper), still solely use oil as their fuel. Namely, in 2024, only circa 2% of the existing number of vessels can use alternative fuels (roughly 8% in terms of gross tonnage) (SIN 2024). As such, it is beyond the scope of this paper to model alternative fuels in relation to scrubber installation. Other alternatives (not for propulsion) have been explored but are currently impractical; these include solar panels, vertical wind turbines, balloons with helium, and kites (Yildirim 2021).

[3] There is also negative network externality from peer effect, but it is not relevant to this paper, as green investment usually relates to positive externality.

[4] Fleet data are available only at a monthly frequency. We apply the Chow-Lin method to the monthly time series to transform them into a weekly time series. The robustness of the method to unit roots is discussed in Silva and Cardoso (2001).

[5] We use information about the typical vessel in a given segment in line with Clarksons' SIN's specifications—which is considered the biggest and most commonly used data source in the shipping industry.

[6] Very Large Crude Carriers (VLCC) vessels have a typical transport capacity of 318,000 DWT; Suezmax of 157,000 DWT; Aframax of 115,000; Panamax of 74,000 DWT; and Handysize of 38,000 DWT. Those vessels are associated with the transportation of crude oil. Capesize vessels have a typical transport capacity of 180,000 DWT and are mainly associated with the transportation of iron ore and coal.

[7] Furthermore, since the available data for time-charter rates from Clarksons' SIN are provided at a segment and not at a company level, it is not feasible to include vessel- or company-specific variables that quantify financing constraints. This approach is in line with the shipping asset pricing and investment literature (e.g., Alizadeh and Nomikos 2007; Kalouptsidi 2014; Greenwood and Hanson 2015).

[8] There are no available time-series data for dry bulk and tanker vessels which are specifically fitted with alternative technologies. As such, and in relation to footnote 2, it is not feasible to incorporate in the model an additional explanatory variable to capture the potential effects of other technologies. However, ESTs aim at reducing the energy (i.e., fuel) usage of vessels and not on eliminating SOx emissions. In other words, unless a scrubber is installed or VLSFO or an alternative fuel with zero SOx emissions is burnt by the vessel, SOx are still emitted. Since vessels capable of burning alternative fuels are an insignificant fraction of the tanker and dry bulk fleet (see footnote 2), even if the vessel is equipped with an EST, scrubber installation and, in turn, the investment dilemma described in this paper is still crucial and highly topical to the industry and policy makers.

[9] The only exemption is the value of 0.78 for $income_{suezmax}$.

[10] The results are available upon request by the authors.

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Appendix A

Literature Review on Scrubber Installation

Table A1 is an incomplete summary of the literature on the financial aspects of scrubber installation. Overall, there is no common view in the literature regarding the exact criteria that drive the decision for scrubber installation rather than using VLSFO. In fact, those criteria vary largely based on the vessel type, route, and assumptions made in the studies. For example, in terms of fuel savings, Jiang et al. (2014) find that marine gas oil (MGO) yields higher NPVs than scrubbers when the fuel price differential does not exceed 231 Euros (around 252 USD) per ton. In comparison, Zhu et al. (2020) argue that MGO is more appealing

TABLE A1 | Summary of literature related to the financial aspects of scrubber installation.

Literature	Methodology	Variables	Conclusions
Abadie et al. 2017	Net present value (NPV), stochastic modelling	Remaining lifetime of the vessel (lifetime), fuel price, emission control area (ECA)	The remaining lifespan of the vessel is the most critical factor. Installing scrubbers slightly increases fuel consumption and emissions.
Andersson et al. 2020	Lifecycle analysis (LCA), sensitivity analysis, cost assessment, calculation of payback period	Fuel price	Open-loop scrubbers have a slightly shorter payback period (0.4–0.5 years) compared to closed-loop scrubbers across various scenarios.
Bekdaş et al. 2023	Estimation of NPV and payback period	Vessel type, interest rate, lifetime, fuel price	Choosing VLSFO for dry bulkers, hybrid scrubbers for oil tankers, open-loop scrubbers for containerships, and hybrid scrubbers for Roll-on Roll-off ships is typically economically beneficial in most situations.
Jang et al. 2020	LCA (construction, operation, maintenance, and scrapping)	Vessel type, lifetime	Vessel age and power significantly affect a scrubber's emission reduction level and economic viability.
Jiang et al. 2014	Cost–benefit analysis, calculation of NPV	Fuel price, lifetime, interest rate	The price difference between marine gas oil (MGO) and HSFO plays a crucial role in this decision. MGO generally yields higher NPVs than scrubbers when the fuel savings are below 231 Euros per ton. Installing scrubbers on new vessels is more advantageous than retrofitting older ones. Vessels with less than 4 years of remaining lifespan are not suitable for scrubber installation.
Karatuğ et al. 2022	Calculation of NPVs and payback period	Vessel type, interest rate	The discounted payback period is calculated to be 0.34 years at a 5% discount rate and 0.37 years at an 8% discount rate, demonstrating why scrubber installations are profitable for shipping companies.
Huang and Hua 2022	Calculation of NPV	Fuel price, interest rate, speed, ECA, freight rate, lifetime	A speed differentiation policy reduces the costs associated with the VLSFO option, thereby reducing its cost disadvantage compared to scrubbers. Additionally, a lower discount rate would favour the scrubber option.
Jee 2022	Lifecycle analysis, NPV calculation	ECA, lifetime, fuel price, interest rate	An empirical study on 72,100 gross-ton cargo vessels indicates that closed-loop scrubber systems are the most cost-effective and environmentally friendly compared to open-loop or hybrid systems.
Lunde Hermansson et al. 2024	Calculation of payback period, simulation of the activity of the global scrubber-fitted fleet	Fuel price, operational costs	After 5 years of scrubber installation, at least 95% of vessels with the most common open- and closed-loop scrubber systems reach breakeven. However, marine ecotoxicity damage costs suggest that private economic benefits may harm marine environmental health.
Panasiuk and Turkina 2015	Calculations of NPV, payback period, and the rate of return	ECA, lifetime, interest rate, fuel price (current and previous prices)	The difference in fuel prices is the key parameter influencing the profitability of the investment.
Reynolds et al. 2011	Life cycle analysis, calculation of NPV, payback period and internal rate of return, sensitivity analysis	ECA, vessel type, fuel price, interest rate	Scrubbers consistently offer significant cost savings, with positive NPVs in all scenarios. The greatest benefits occur for routes spending the most time in ECA zones.
Wu and Lin 2020	Cost benefit analysis	Fuel price, lifetime	For the first 3.3 years, the scrubber installation has a higher cost–benefit ratio than the VLSFO strategy. Therefore, the VLSFO strategy, which emits fewer pollutants, is more suitable for vessels with a remaining lifetime exceeding 3.3 years.
Yang and Zou 2023	Cost assessment, sensitivity analysis	ECA, speed, vessel fuel type	Currently, the most economical choice is to continue using HSFO with installed scrubbers. However, when the proportion of sailing time within the ECA exceeds 47%, methanol becomes the best option for both economic and environmental benefits.
Zhu et al. 2020	Cost benefit analysis, sensitivity analysis, calculation of NPV and annual unit cost	Fuel price, interest rate, lifetime	Scrubbers are generally more appealing, except in two scenarios where VLSFO is preferred. Specifically, a scrubber becomes less attractive when VLSFO and MGO price differential is $56 per ton or less, and when HSFO and MGO price differential is $16 per ton or less.
Zis et al. 2022	Calculation of NPV and payback period	Vessel type, fuel price, speed, ECA	Scrubbers are more economically beneficial with higher fuel prices and increased sailing time. The paper shows that the potential for speed differentiation inside and outside ECAs has diminished.

Note: The methods and variables in the table only include those related to financial investment.

if the fuel price differential is lower than 56 USD per ton. In terms of payback period, Karatuğ et al. (2022) suggest that the discounted payback periods of scrubber investment are 0.34 and 0.37 years under 5% and 8% rates of return, correspondingly. Wu and Lin (2020) conclude that the scrubber option is preferred when the remaining payback period is over 3.3 years. Therefore, the significant discrepancy in the findings calls for robust and sophisticated methods that can address the multiple causalities between green investment and market uncertainty.

According to Table A1, the studies have employed a variety of methods, but most—if not all—are based on strong assumptions and there is a lack of data-driven methods. The most frequently used methods include lifecycle analysis; cost benefit analysis; sensitivity analysis; estimation of net present value (NPV) and payback period.

Lifecycle analysis typically examines the costs associated with the entire lifecycle of a scrubber system, encompassing construction, operation, maintenance, and disposal (Andersson et al. 2020; Jang et al. 2020; Jee 2022; Reynolds et al. 2011). This method more thoroughly evaluates the investment decision, as opposed to merely considering capital investment and operational profit.

Cost–benefit analysis goes beyond cost consideration by comparing it with the accrued benefits, providing a more robust assessment than mere cost evaluation (Jiang et al. 2014; Wu and Lin 2020; Zhu et al. 2020). Sensitivity analysis identifies the key variables that influence the investment decision in scrubber installation (Andersson et al. 2020; Reynolds et al. 2011; Yang and Zou 2023; Zhu et al. 2020). It is an effective tool for navigating market uncertainties, as the decision to install a scrubber versus using VLSFO can fluctuate depending on changes in interest rates and fuel prices. Sensitivity analysis determines under which conditions one decision may be favoured over another.

Lastly, the calculation of NPV and payback periods is a common approach in the literature (indicatively, Bekdaş et al. 2023; Karatuğ et al. 2022; Panasiuk and Turkina 2015; Zis et al. 2022). This method accounts for the time value of money by considering the discount rate on investments, offering a more substantial basis than simple, non-discounted cost calculations. Given that shipping investments can span up to 20 years, discounting future earnings to their present value is crucial.

All these methods make assumptions about the inputs and test whether a scrubber installation is worthwhile based on those. None of the studies have observed the real financial benefits from scrubber investment. Instead, our paper applies an evidence-based, rigorous econometric framework, VECM, with actual observations on the freight income generated by scrubber installation (TC premium).

Appendix B

Diagnostic Tests

TABLE A2 | Granger causality tests.

	F-statistics															
	ΔI_{vlcc}	ΔS_{vlcc}	ΔI_S	ΔS_S	ΔI_A	ΔS_A	ΔI_P	ΔS_P	ΔI_H	ΔS_H	ΔF_T	ΔI_c^A	ΔI_c^P	ΔS_C	ΔF_D	p
ΔI_{vlcc}	—	1.85[c]	—	—	—	—	—	—	—	—	1.95[c]	—	—	—	—	0.001
ΔS_{vlcc}	3.78[a]	—	—	—	—	—	—	—	—	—	2.34[b]	—	—	—	—	0.003
ΔI_S	—	—	—	1.83 [c]	—	—	—	—	—	—	0.256	—	—	—	—	0.001
ΔS_S	—	—	3.51[a]	—	—	—	—	—	—	—	1.83[c]	—	—	—	—	0.000
ΔI_A	—	—	—	—	—	0.395	—	—	—	—	0.432	—	—	—	—	0.005
ΔS_A	—	—	—	—	1.67[c]	—	—	—	—	—	0.883	—	—	—	—	0.001
ΔI_P	—	—	—	—	—	—	—	1.78[c]	—	—	1.86[c]	—	—	—	—	0.007
ΔS_P	—	—	—	—	—	—	3.86[a]	—	—	—	1.88[c]	—	—	—	—	0.000
ΔI_H	—	—	—	—	—	—	—	—	—	2.89[b]	1.90[c]	—	—	—	—	0.005
ΔS_H	—	—	—	—	—		—	—	3.85[a]	—	1.92[c]	—	—	—	—	0.006
ΔF_T	1.83[c]	3.88[b]	4.88[a]	1.92 [c]	0.986	1.87[b]	5.43[a]	0.457	2.77[b]	1.87[c]	—	—	—	—	—	0.000
ΔI_c^A	—	—	—	—	—	—	—	—	—	—	—	—	—			0.000
ΔI_c^P	—	—	—	—	—	—	—	—	—	—	—	—	—	1.95[c]	2.85[b]	0.002
ΔS_C	—	—	—	—	—	—	—	—	—	—	—	4.56[a]	3.82[a]	—	1.97[c]	0.001
ΔF_D	—	—	—	—	—	—	—	—	—	—	—	—	4.72[a]	4.19[a]	—	0.001

Note: For brevity and to accommodate all data in one table, ΔI_{vlcc}, ΔS_{vlcc}, ΔI_S, ΔS_S, ΔI_A, ΔS_A, ΔI_P ΔS_P, ΔI_H, ΔS_H, ΔF_T, ΔI_c^A, ΔI_c^P, $\Delta S_C, \Delta F_D$, denote $\Delta income_{vlcc}$, $\Delta supply_{vlcc}$, $\Delta income_{suezmax}$, $\Delta income_{aframax}$, $\Delta income_{panamax}$, $\Delta supply_{panamax}$, $\Delta income_{handysize}$, $\Delta supply_{handysize}$, $\Delta fuel_{tanker}$, $\Delta income_{capesize}^{atlantic}$, $\Delta income_{capesize}^{pacific}$, $\Delta supply_{capesize}$, $\Delta fuel_{drybulk}$, respectively. The ECT is derived through normalisation of the cointegrating vector on *Income*. The residual was then checked for stationarity using unit root tests and by inspecting its Autocorrelation Function (ACF). The final column reports estimated t-statistics, which test the null hypothesis that the lagged ECT is not statistically significant in any equation. The remaining estimates correspond to asymptotic Granger F-statistics. The VECM was estimated with an optimally determined SBIC lag structure of 4 for all lagged-difference terms, including restrictions and a constant. Significance levels are indicated by a, b, and c for the 1%, 5% and 10% levels, respectively.