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# Hedging Strategies in Carbon Emission Price Dynamics: Implications for Shipping Markets

**Theodoros Syriopoulos, Efthymios Roumpis * and Michael Tsatsaronis**

Ports Management and Shipping Department, School of Economics and Political Sciences, National and Kapodistrian University of Athens, 15772 Athens, Greece; tsiriop@pms.uoa.gr (T.S.); mtsatsaronis@pms.uoa.gr (M.T.)
* Correspondence: eroumpis@pms.uoa.gr

**Abstract:** The European Union (EU) has agreed to gradually include shipping in the EU emissions trading scheme (EU ETS), which makes shipping companies vulnerable to carbon price fluctuations. The aim of this paper is to investigate the effectiveness of carbon and petroleum futures contracts in managing carbon and bunker risks. We examine the effectiveness of alternative hedging methods, including both static and dynamic approaches, to estimate optimal hedge ratios under single and composite cross-hedge settings. Our results show that carbon future contracts are important for hedging the carbon emission allowances price risk, and Brent oil futures are the most effective instrument for out-of-sample hedging of bunker prices. In addition, the hedging effectiveness indicates that conventional methods outperform the sophisticated models in terms of variance reduction. Our study offers new insights into how the carbon and bunker markets relate to a combination hedging in reducing the joint price risk, which can be used to promote risk management in the market.

**Keywords:** emissions trading scheme; shipping; hedging; carbon emission; bunker risk

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## 1. Introduction

Shipping accounts for almost 3% of the total global greenhouse gas (GHG) emissions annually [1], and it is estimated to increase in the coming years as seaborne trade keeps growing and remains highly reliant on fossil fuels without notable improvements in energy efficiency or sufficient implementation of emission reduction measures. Shipping emissions are expected to increase by between 90–130% of 2008 emissions by 2050 for a range of plausible scenarios [1]. To combat the rapid growth in GHG emissions, several initiatives and regulations have been proposed and implemented at a global and regional level to tackle the rapid growth in GHG emissions.

The International Maritime Organization (IMO), the regulatory body for international shipping, has been devoted to limiting and reducing carbon emissions from the shipping sector since the early 2000s [2]. IMO has undertaken technical studies of the issue and served as a forum for the negotiation of the technical standards, resulting in a number of regulations and policies covering a broad range of important factors that affect the footprint of each ship, including fuel quality, engine efficiency and hull designs. The IMO has decided on several instruments to improve ships' fuel efficiency: the Energy Efficiency Design Index (EEDI), Energy Efficiency Existing Ship Index (EEXI) and Carbon Intensity Indicator (CII)) and market-based instruments are under discussion to be implemented in the coming years [1]). Despite the efforts undertaken, the progress in IMO is unsatisfactory, as GHG emissions from shipping are not decreasing, and therefore, regional initiatives have been recently adopted in the EU.

Along with the global initiatives undertaken by the IMO, in July 2021, the European Commission (EC) proposed a basket of measures, namely the "Fit for 55" legislative package that aims to include maritime transport in the EU climate efforts. The package supports the EU commitment to the 'European Green Deal' target for a 55% reduction in the EU's GHG emissions by 2030 compared to 1990 and for climate neutrality in Europe by 2050 [3]. The inclusion of shipping into the EU Emissions Trading Scheme (EU ETS) is one of these proposals, and together with four other proposals, it seeks to steer the EU maritime sector towards decarbonization. This basket of measures also contains the 'FuelEU Maritime' initiative aiming to increase demand and the deployment of renewable alternative transport fuels ('FuelEU Maritime Regulation') and remove the current taxation exemption regarding fuel used by ships ('Energy Taxation Directive'). The EU ETS commenced its operations in 2005 and is regarded as one of the earliest and most significant carbon markets [4] with the largest trading volume in the world [5].

The scope of EU ETS was first referred to about 12,000 stationary installations, covering approximately 40% of the European $CO_2$ emissions [6]. In 2012, the aviation sector was added to the EU ETS [7]. Critical implications of the inclusion of the shipping sector into the EU ETS were deduced from previous inclusion of aviation in the EU ETS, proposals from the EU institutions (Parliament, Commission and Council) and input from market practitioners in the shipping industry [8]. From 2024, the EU ETS would apply to (i) vessels of 5000 gross tonnage (GT) and above, regardless of flag, reflecting the current application of the EU Monitoring, Reporting and Verification Regulation 2015/757 (MRV Regulation—The MRV database was established by the EU MRV [9] for the monitoring, reporting and verification of $CO_2$ emissions within the European Economic Area (EEA) from maritime transport; (ii) 100% of the emissions from intra-EU maritime voyages, 50% of emissions from all inbound and outbound voyages between the EU and non-EU ports, and 100% of emissions from ships at berth in EU ports; (iii) only carbon dioxide ($CO_2$) emissions. However, methane ($CH_4$) and nitrous oxide ($N_2O$) emissions are to be included only as of 2026.

The EU ETS is considered an efficient Market-Based Measure (MBM) to combat climate change. The so-called market-based measures (MBMs) apply the "polluter pays principle", in which the polluter bears the costs of its emissions. These measures can range from bunker levies and trading emissions to environmental taxes, inter alia, and provide incentives for the polluter to reduce emissions [10]. It sets a maximum quantity of GHG that can be emitted and issues a limited number of tradable allowances not exceeding the level of the cap. Shipping companies are then allowed to buy or sell emission allowances on the market. The acquisition of emission allowances gives the right to its holder to emit the equivalent of one metric ton of $CO_2$ into the atmosphere. The integration of maritime transport in the EU ETS makes it more expensive for shipping companies to emit $CO_2$ and ensure that they take account of the costs of emissions when making commercial decisions. Over the long run, shipping companies will seek to minimize costs by investing in low-carbon technology alternative energy and adopting the most cost-effective abatement solutions because the cost of transition is very high [11]. However, in the short run, shipping companies have acknowledged the importance of managing carbon price risk and trying to mitigate it by engaging the appropriate hedging strategies.

For the purpose of carbon emission risk management, a shipowner can set up a long hedging position by buying carbon futures contracts. The Shipowner has a short carbon position, as it represents the amount of $CO_2$ emitted by the ship and the associated carbon emission cost, and he is worried that carbon prices may increase over the next scheduled voyage and thus reduce the profit from the voyage. To manage their exposure to carbon price fluctuations, a shipowner can buy carbon futures contracts. The hedging strategy should take into account the relationship between carbon spot and futures prices, the duration of the voyage and the expected amount of carbon emissions. Fuel consumption and, therefore, the emitted $CO_2$ by a ship depends on the distance traveled, vessel size, hull design and weather conditions, inter alia [12–15].

The shipping industry expects a significant cost increase from the inclusion of shipping in the EU ETS; however, the economic impact will largely vary depending on the price of emission allowances, the geographical scope of the system, the ship type and the energy efficiency of ships and operations [16]. The volatility of carbon prices affects shipping companies' emission decisions, as when the carbon price decreases, a company's cost of purchasing additional allowances decreases, and the company can emit more carbon emissions in exchange for more economic benefits. In contrast, when the carbon price increases, a company will choose to reduce the freight volume and reduce carbon emissions if the marginal cost of purchasing additional allowances overreaches the marginal benefit generated by transporting cargo [17]. Empirical evidence indicates that carbon prices at a high enough level of around USD 120/ton carbon can accelerate the intake of abatement operational and technological improvements in the shipping fleet [1]. Moreover, the impact of EU ETS is not expected to be the same across the different shipping sub-sectors. For example, Roll-on/Roll-off (RoRo) and Roll-On/Roll-Off/Passenger (RoPax) vessels would be penalized due to their high fuel consumption per transport work in comparison to oil tankers and bulkers [18]. Concerns regarding the stability of the shipping sector have also been raised due to the carbon price volatility and the increased risk of administrative, technical and operational challenges from the inclusion of shipping into the EU ETS [19].

The motivation for this study stems from the fact that the extension of EU ETS to the shipping industry is currently one of the most thought-provoking issues among industry practitioners and academics. With the aim of improving risk management in the carbon and bunker markets, we initially examine the performance of a single instrument hedging strategy on carbon allowances prices, and subsequently, we provide new insights into how carbon and bunker prices relate to a combination hedging. The underlying assets in the carbon markets are very different from those in the other financial markets, and they are still not well understood.

Unlike conventional financial instruments, which pay interest, dividends or other payments, carbon allowances do not provide interim cash flows; instead, holders can simply collect the value from the resale price, which is determined by demand and supply forces [20,21]. Ref. [22] focused on the complex interaction among policy targets, market rules and dynamic technology costs to investigate price dynamics and risk factors in the carbon emissions markets. Ref. [23] examined the carbon emissions within the nexus of trade dynamics, energy consumption and economic growth. They conclude that trade liberalization is a key determinant of environmental quality, which significantly contributes to $CO_2$ emissions, energy consumption, and economic growth. Despite the novel features and rapid growth of carbon emission markets, our study contributes to the limited number of studies in the literature that focus on risk management and optimal hedging in the carbon emission markets. Previous studies on carbon markets by [24–26] focused more on the dynamics between carbon spot and futures markets and examined the effectiveness of alternative hedging methods.

Most research in shipping risk management uses single instruments or cross-hedging strategies to hedge either freight risk or bunker risk. However, to the best of our knowledge, there exists no research that estimates the composite instrument hedge for optimal futures hedging of carbon and bunker risks. In contrast, there is a significant number of studies in the literature on different aspects of shipping freight derivatives, hedging strategies and hedging performance [27–29]. Ref. [30] examined cross-hedging techniques using petroleum futures contracts for hedging bunker risk. In a related study, Ref. [31] investigated the dynamics of the relationship between oil futures and the hedging effectiveness of future contracts among different fuel derivatives.

In this paper, we develop hedging strategies by considering the interactions between carbon spot and futures prices from the European Union Allowances (EUA) markets; we apply four econometric models to estimate optimal hedge ratios (OHR) and assess their performance using hedging effectiveness (HE) measures. Furthermore, we examine the issue of carbon risk hedging for ship emissions related to freight voyages departing from non-European ports and arriving at European ports. For the purpose of our analysis, we have chosen specific shipping market segments that serve some of the most active European-related seaborne trade. We estimate the fuel consumption and corresponding $CO_2$ emissions of benchmark vessels operating in these trading routes to obtain an estimation of carbon allowance cost. Then, we address the hedging problem associated with price fluctuations in carbon and bunker markets.

Because of the urgency of regulations of carbon emissions not only in the US and the EU but also in other parts of the world, this paper makes several contributions to the literature on hedging applications for carbon risk management that are both practical and academically significant, specifically in shipping businesses. First, as far as the author is aware, it is the first to explore an optimal hedging strategy that can be used to manage the exposure of a shipping company to both the $CO_2$ and fuel price risks. Second, these findings suggest that, despite the peculiarity of the carbon market, the methods, techniques, ideas, and concepts employed in finance may still be used in the analysis of such markets, with some changes. Third, it is a beneficial instrument for financial risk management in the shipping sector, providing a comprehensive approach to shipping firms' operational and financial departments.

The remainder of the article is organized as follows. Section 2 presents a brief review of the literature on carbon markets, with a focus on risk management and the challenge of implementing a Carbon ETS in the shipping sector. The methodology is developed in Sections 3 and 4. Section 3 outlines the methodology of minimum variance hedge strategies, the econometric models for estimating the OHR and the measurements for assessing the hedging performance. Section 4 provides the details of a case study for carbon emissions and bunker risk management in shipping. Section 5 describes the data and its descriptive statistics. Section 6 discusses the results from the various hedging models and the hedging effectiveness is evaluated. Finally, Section 7 concludes the paper.

## 2. Literature Review

The Kyoto Protocol was signed in 1997 by members of the United Nations Framework Convention on Climate Change, making Carbon Emissions Trading (CET) rights the property of an emergent financial asset [32]. Since then, international carbon markets have played a key role in reducing GHG emissions. Emission trading programs have been launched with the UN Certified Emissions Reduction (CER), the Chicago Climate Exchange (CCX), the EU Emissions Trading System (EU ETS), the Japan Voluntary Emissions Trading System (JVETS) and the China Certified Emissions Reduction (CCER) are all part of the market [33]. So far, the EU ETS is the most established and mature carbon trading market [32], covering around 50% of emissions from more than thirty countries in Europe [34]. The EU ETS is considered one of the most important policies at the EU level and the backbone of the EU's climate policy to achieve compliance with the Kyoto Protocol.

Although the carbon markets have gained eminence for carbon-releasing companies, international investors and policy-makers, the studies dealing with hedging techniques and optimal hedging ratios in carbon risk management are limited in the literature. Ref. [24] documented the high correlation between carbon spot and futures markets, strong information spillover between these markets and the potential benefits for the investors who would decide to invest in both carbon spot and futures markets to hedge risk. Ref. [25] examined the hedging performance in the European carbon markets and their results indicate that the static hedge ratios generated from the simple ordinary least squares provide the greatest variance reduction in most cases against the most advanced approaches. In addition, Ref. [26] documented significant gains in using Markov regime-switching models for generating optimal hedging in carbon emission markets than single regime hedging models. Refs. [35,36] investigated the carbon market extensively, focusing on financing, pricing, and risk hedging measures. Ref. [37] used the multivariate GARCH and OLS models, as well as the naive approach, to calculate the optimal hedging ratios (OHR) for the European Climate Exchange. When adjustment costs are not included, their results show that dynamic hedging produces higher returns (in terms of lowering portfolio variation) than static hedging. Overall, the lack of studies on the calculation of hedge ratios for carbon assets, as well as the novelty of the carbon market, give strong impetus for us to investigate OHR and carbon risk hedging techniques.

Until recently, the risk management of shipping companies was focused on managing two primary risks related to bunker risk and freight rates risk. These two risk areas are relatively familiar, and many shipping companies already have methods, procedures, and tools in place to track, monitor, report, and hedge against them [27–31]. The inclusion of shipping into the EU ETS has entered a new major risk for shipping companies, and that is carbon risk. Carbon risk is becoming increasingly prevalent as the emission trading schemes are coming into effect globally and the shipping industry is being incorporated into them. It is therefore increasingly important for shipping companies to accurately estimate fuel consumption, adjust fleet operation; for example, slow steaming, and consistently evaluate vessel emissions in order to achieve emission reduction in the short term and develop effective risk management strategies [16].

The literature has only a few studies on maritime ETS. Ref. [38] thoroughly examined and analyzed all prospective MBMs (including the maritime ETS) presented to the IMO. Ref. [39] assessed the impact of adopting an open maritime ETS on a variety of fronts, including global trade patterns, net-exporting nations, and market concentration in the maritime sector. Ref. [40] analyzed the prospect of including the shipping sector in the present EU ETS and contrasted this idea with alternatives such as a bunker charge system and the Maritime Sector Crediting Mechanism. Ref. [41] investigated the effects of a cap-and-trade system on shipping lines and European ports. This study discovered significant and diverse impacts in several settings. To analyze the organizational and operational effects of the maritime ETS on shipping enterprises, [42] undertook a case study involving ship operators, showing that shipping companies are optimistic about the potential performance of maritime ETS. Ref. [43] examined the economic and legal implications of adding shipping in the present EU ETS. They contended that such an endeavor would be impossible to accomplish a cost-effective emission reduction while still complying with existing international legislation. Ref. [44] conducted a qualitative study on the geographical extent of maritime ETS. Ref. [45] investigated the dynamic reliance and information spillovers between the carbon financing market and shipping using wavelet analysis and the spillover index methodologies.

Most research on carbon markets has mainly focused on the interactions of carbon markets with financial and energy markets. The dynamic linkages and spillover effects of the carbon market with energy markets, including coal, oil, natural gas and electricity, have been investigated through various techniques, for example, multivariate GARCH models [46–48]; the wavelet approach [49,50]; Granger causality tests [51]; and network modeling [52]. Moreover, the interactions between the carbon markets and non-energy financial assets have been investigated, including the currency market [53], stock market [54,55] and bond market [49,56].

In addition to the above studies, the existing literature also examines the drivers of carbon allowance prices. The price of EUAs is governed by basic demand and supply, just like the price of any other tradable asset. However, carbon pricing determinants are distinct. The price can be decided by fuel costs, weather, and economic growth on the demand side, but it is set by regulatory authorities on the supply side, which is a unique aspect of the market [57]. Refs. [58–62] all corroborated the relationship between energy and EUA pricing. Using the Granger causality technique, Ref. [63] discovered evidence that power costs are connected to $CO_2$ pricing. Ref. [64] studied the equilibrium link between carbon futures prices and fundamentals such as energy spreads for electricity generation, the EuroStoxx 50, the Eurostat index of industrial production, the oil price, and a temperature index using cointegration techniques. Furthermore, the relationship between $CO_2$ emissions and macroeconomic factors is among the most researched themes of environmental economics. Ref. [65] examines the macroeconomic determinants of European carbon allowances prices. Ref. [66] examined the short-run and long-run linkages between exchange rate, $CO_2$ emissions and GDP. They showed that currency devaluation has an expansionary effect that enhances economic growth at the cost of high energy consumption and $CO_2$ emissions. The relationship between environmental degradation and economic growth has gathered considerable attention from researchers [67–69]. Their empirical findings indicate that developed countries pursue policies, such as carbon taxation and carbon pricing, to mitigate environmental degradation, while developing countries seem to ignore these serious problems, following less stringent environmental policies.

## 3. Methodology

The inclusion of shipping into the EU ETS introduces uncertainty and increases the cost of maritime transport, especially for shipping companies that are engaged in EU voyages and voyages, which include port calls in European ports. We assume that a shipping company is vulnerable to fluctuations in carbon prices and wishes to lock in the costs of future purchases of carbon allowances. Therefore, it aims to hedge against a possible rise in the price of $CO_2$ by using futures contracts, which are highly correlated with the spot market. A common approach to hedging strategies is based on the minimum-variance hedge ratio, i.e., the hedge ratio that minimizes the variance of the hedged portfolio [26,70–72]. In this context, the shipping company decides on the optimal number of futures contracts that minimize the risk of the combined portfolio of the $CO_2$ spot and futures. Specifically, the OHR reflects the number of long positions in carbon allowances futures contracts that a shipping company should optimally hold for each unit of carbon allowances that will be purchased in the future.

We initially consider the case of the single hedging strategy for the $CO_2$ price risk. Afterward, we focus on a general portfolio model to demonstrate how an optimal hedging strategy can be used to manage the exposure of the shipping company to both the $CO_2$ and fuel price risks. In the presence of multiple price risks, it is essential to the development of hedging strategies that use multiple futures contracts and manage correlated risks. Following an examination of hedging approaches on different sources of risk, we focus on the impact of carbon and fuel price risks in this research because a single hedging instrument cannot entirely remove all uncertainty associated with these costs. Our interest here is to consider composite cross-hedging strategies in which we assess the performance of future instruments for jointly addressing the carbon allowances and bunker prices hedging problem.

It is useful to distinguish two board categories of models that are used in estimating the OHR: (a) static hedge ratio and (b) dynamic hedge ratio. In this article, we employ four econometric models for the joint distribution of spot and futures returns and thus estimate the covariance matrix to ultimately determine the hedge ratios. The Ordinary Least Square (OLS) model and the Error Correction model (ECM), an "augmented" variant of OLS, are used to estimate a static hedge ratio. In addition, two models are used to estimate dynamic hedge ratios: the Asymmetric Dynamic Conditional Correlation (ADCC) [73] and the Student's *t*-copula [74,75] models, which are able to support a variety of dynamic dependence structures between spot and futures returns [76].

The methodology section includes two parts. First, the novel methodology for calculating $CO_2$ emission costs and the relationship between ship fuel consumption and $CO_2$ emissions is presented. Second, the methodology for estimating hedge ratios is presented, beginning with a single-hedge ratio that investigates only the risk reduction associated with exposure to $CO_2$ price risk and progressing to a multi-hedge framework that exploits the dependence between future instruments in both bunker and carbon markets for managing the risks associated with bunker and carbon allowances. Our hedging strategies are built on static and dynamic settings with respect to the relationship between spot and future prices, using conventional and recently developed models in order to detect how the dynamic correlations influence the optimal hedging results.

### 3.1. $CO_2$ Emission Cost

The total amount of $CO_2$ emitted by a ship is proportional to its fuel consumption at sea and within ports at berth. Fuel consumption highly depends on a ship's sailing speed, where it is widely recognized that the fuel consumption per time unit of a ship is a cubic function of speed [77]. Except for the speed, fuel consumption and therefore, the $CO_2$ emissions depend on the distance traveled, vessel size, hull design and weather conditions, inter alia [12–15]. In this article, we have chosen the following approximation for the $CO_2$ emissions calculation of a round voyage:

$$E_{CO_2} = \varepsilon_u \cdot D_{ij} \cdot \left[ V^u_{S,l,ij} \cdot \frac{d_{ij}}{s_l} + B^u T_P \right] + \varepsilon_u \cdot D_{iq} \cdot \left[ V^u_{S,b,jq} \cdot \frac{d_{jq}}{s_b} \right]$$

where $\varepsilon_u$ is the emission factor, which indicates the amount of $CO_2$ emission for every metric ton of fuel $u$ consumed by the ship. The emission factors of the most consuming fuel types are listed in Table 1. The international shipping fleet mainly consumes Heavy Fuel Oil (HFO) and Marine Diesel Oil (MDO). The alternative fuel of Liquified Natural Gas (LNG) has the advantage of a lower emission factor, along with other attractive features, such as the lack of sulfur and the production of more energy per unit weight than fossil fuels. However, the main disadvantage of LNG as a fuel for vessels is the release of methane, which is many times more potent than $CO_2$ [78,79]. $V^u_{S,l,ij}$ and $V^u_{S,b,jq}$ are the fuel consumptions of the vessel, expressed in tons per day for specific sailing speed, when sailing on laden voyage between ports $i$ and $j$, and ballast voyage between ports $j$ and $q$, respectively. $d_{ij}$ and $d_{jq}$ denote the sailing distance between ports $i$, $j$ and $j$, $q$ in nautical miles. $s_l$ and $s_b$ express the operational speed of the vessel, measured in nautical miles per hour (knots), when it is laden with cargo and ballast on the return leg of the voyage, respectively. Fuel consumption in ports is calculated by multiplying the estimated daily consumption in tons, $B^u$, of fuel $u$ and the time in days that the ship is at berth, $T_P$. $D_{ij}$ and $D_{iq}$ are dummy variables that take the values of 1 or 0.5 whether the port calls of the round voyage are between two EU ports or one of them is outside of the EU, respectively. This provision is in line with the EU proposal to include the emissions from ships in the EU ETS, in which emissions between EU ports count for 100% and emissions from non-EU ports to EU ports count for 50%.

**Table 1.** Emission factors per marine fuel.

| Fuel Type | Emission Factor (MT $CO_2$/MT Fuel Consumption) |
|---|---|
| Heavy fuel oil (HFO) | 3.114 |
| Marine diesel oil (MDO) | 3.206 |
| Liquified Natural Gas (LNG) | 2.750 |

Source: [2] (p. 74).

Then, the $CO_2$ emissions cost of a round voyage, $C_{CO_2}$, could be estimated as the product of unit price of $CO_2$ emissions, $P^s_{CO_2}$, and the $E_{CO_2}$ emission volume:

$$C_{CO_2} = P^s_{CO_2} \cdot E_{CO_2}$$

where $P^s_{CO_2}$ is the spot price of one tonne of $CO_2$ allowance trading in the secondary market.

### 3.2. Optimal Hedge Ratio (OHR) Estimation

#### 3.2.1. Single Instrument Optimal Hedge Ratio

We assume that the objective of a shipping company is to eliminate its exposure to carbon allowance price risk and, therefore, it uses a single instrument to hedge; thus, the OHR $\lambda$, can be defined solely on the minimum variance of payoff from the hedged position [80] by taking imperfect correlations into account. To determine optimal hedging, let $s_{t,CO_2}$ and $f_{t,CO_2}$ denote the spot and futures one-period logarithmic returns at time $t$

respectively, and let $\lambda_{t,CO_2}$ be the hedge ratio, defined as the number of future positions held at time $t$. The return of the hedged portfolio:

$$r_t = s_{CO_2,t} - \lambda_{CO_2,t} f_{CO_2,t}$$

where $r_t$ is the return on holding the portfolio between $t-1$ and $t$. The variance of the returns of the hedged portfolio, conditional on the information set available at time $t-1$, is given by:

$$var(r_t) = var\left(s_{CO_2,t}\right) + \lambda^2_{CO_2,t} var\left(f_{CO_2,t}\right) - 2\lambda_{CO_2,t} cov\left(s_{CO_2,t}, f_{CO_2,t}\right)$$

where $var\left(s_{CO_2,t}\right)$, $var\left(f_{CO_2,t}\right)$ and $cov\left(s_{CO_2,t}, f_{CO_2,t}\right)$ are the conditional variance and co-variance of spot and future returns, respectively. The OHR is defined as the value of $\lambda_t$, which minimizes the conditional variance of hedged portfolio returns on the given information set, as follows:

$$\lambda^* = \frac{cov\left(s_{CO_2,t}, f_{CO_2,t}\right)}{var\left(f_{CO_2,t}\right)}$$

#### 3.2.2. Composite Instrument Optimal Hedge Ratio

In composite hedging, we wish to hedge the risk due to the typically wide fluctuation in carbon allowance and fuel prices. When using two future contracts to hedge both the carbon allowance and bunker price risk, the return of the portfolio $r_t$ is given by:

$$r_t = s_{CO_2,t} + s_{B,t} - \lambda_{CO_2,t} f_{CO_2,t} - \lambda_{B,t} f_{B,t}$$

where $s_{B,t}$ and $f_{B,t}$ are the spot bunker fuel and petroleum futures price one-period logarithmic returns at time $t$, respectively. $\lambda_{t,CO_2}$ and $\lambda_{B,t}$ are the hedge ratios at time $t$, defined as the optimal futures position per unit of the spot asset at time $t$. The variance of $r_t$ may be written as:

$$\begin{aligned} var(r_t) = \; & var\left(s_{CO_2,t}\right) + var(s_{B,t}) + \lambda^2_{CO_2,t} var\left(f_{CO_2,t}\right) + \lambda^2_{B,t} var(f_{B,t}) - 2cov\left(s_{CO_2,t}, s_{B,t}\right) \\ & -2\lambda_{CO_2,t} cov\left(s_{CO_2,t}, f_{CO_2,t}\right) - 2\lambda_{CO_2,t} cov\left(s_{B,t}, f_{CO_2,t}\right) - 2\lambda_{B,t} cov\left(s_{CO_2,t}, f_{B,t}\right) \\ & -2\lambda_{B,t} cov(s_{B,t}, f_{B,t}) + 2\lambda_{CO_2,t}\lambda_{B,t} cov\left(f_{CO_2,t}, f_{B,t}\right) \end{aligned}$$

where $var(s_{B,t})$ and $var(f_{B,t})$ represent the conditional variances of spot bunker fuel returns and petroleum futures returns, respectively. Minimizing the above equation with respect to $\lambda_{CO_2,t}$ and $\lambda_{B,t}$, the optimal number of future contracts or the OHR in the portfolio can be obtained by minimizing the portfolio's conditional variance. To investigate which of the petroleum futures contracts are the best hedging instruments for bunkers, the OHR and the HE assessments are performed for the different pairs of Rotterdam bunker prices and petroleum futures contract prices.

### *3.3. Hedging Models*

#### 3.3.1. Ordinary Least Square (OLS) Model

The simplest approach to obtain the OHR involves regressing percentage changes in spot prices on percentage changes in futures prices using OLS. In this setting, the slope coefficients of OLS model are widely utilized to generate the time-invariant hedge ratios [81]. We can write the regression equation in the following way:

$$s_t = \alpha_0 + b f_t + e_t$$

where the estimate of the minimum variance hedge ratio $\lambda$ is given by $b$. When applying more than one instrument, the regression equation can be written as:

$$s_t = \alpha_0 + \sum_{i=1}^{n} b_i f_t + e_t$$

where the values of $b_{i,t}$ are the hedge ratios corresponding to the related future contracts.

3.3.2. Error Correction Model (ECM)

The Error Correction (ECM) model is used in response to the downsides of using the OLS hedge ratio that ignores short-run dynamics and the cointegrating relationship between spot and futures prices. The empirical literature advocates that the ECM model is a better alternative to the classical OLS model and may lead to the estimation of more accurate hedge ratios [70,72,82]. The ECM model can be defined as:

$$s_t = \alpha + bf_t + \gamma u_{t-1} + \sum_{i=1}^{n} \varphi_{s_i} s_{t-i} + \sum_{j=1}^{m} \varphi_{f_i} f_{t-j} + e_t$$

where $u_t$ is error correction term $u_t$ obtained from the cointegration regression given by:

$$ln(S_t) = \alpha + \psi ln(F_t) + u_t$$

The estimate of $b$ denotes the OHR, while the lag orders of $i$ and $j$ can be determined by using the Akaike information criterion (AIC).

3.3.3. Asymmetric Dynamic Conditional Correlation (ADCC) Model

The ADCC model is a popular and widely used model from the family of multivariate GARCH-type models. The model allows a two-stage estimation procedure, which simplifies the estimation of conditional variances and correlations. In the first stage, a univariate GARCH model is estimated for each of the variables. In the second stage, the standardized residuals are introduced as inputs to estimate dynamic correlations. The DCC model captures the dynamics of time-varying conditional correlations, with the covariance matrix, $H_t$, specified as:

$$H_t = D_t R_t D_t$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$ is an $m \times m$ diagonal matrix with the square roots of the conditional variances in the diagonal; and $R_t \equiv \{\rho_{ij}\}_t$ is the time-varying conditional correlations matrix. An appealing property is that the ADCC model allows for a time-varying correlation structure parameterization. The first-order univariate GARCH process is indicated in the following equation:

$$h_{i,t} = \omega_i + \alpha_i \cdot \varepsilon_{i,t-1}^2 + \beta_i \cdot h_{i,t-1}$$

where $i = 1, 2, \ldots, m$, indicates the $i$-th equation in the vector autoregressive (VAR) model and $h_{i,t}$ is the conditional variance of the error term, $\varepsilon_{i,t}$, of the $i$-th equation, obtained from the first stage of the estimation procedure. In the second stage, the vector of the standardized residuals is employed to develop the ADCC correlation specification:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} - g\overline{\Xi} + \theta_1 \eta_{t-1}\eta'_{t-1} + \theta_2 Q_{t-1} + g\xi_{t-1}\xi'_{t-1}$$

and

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where $\overline{Q} = E[\xi_t \xi'_t]$, the unconditional covariance of the standardized residuals, is obtained from the first stage of the estimation process and $Q_t^* = (diag(Q_t))^{-1/2} = diag\left(1/\sqrt{q_{11,t}}, \ldots, 1/\sqrt{q_{mm,t}}\right)$ is a diagonal matrix composed of the square root of the diagonal elements of $Q_t$. $\theta_1$ and $\theta_2$ are scalar parameters, $\eta_t \left(\eta_t = D_t^{-1}\right)$ is the standardized residual matrix and $Q_t$ is the covariance matrix of $\eta_t$. The parameters $\theta_1$ and $\theta_2$ capture the effects of past shocks and past dynamic conditional correlations on current dynamic conditional correlations. The parameter $g$ introduces the asymmetric effects into the model; $\xi_t = I[\eta_t < 0] \circ \eta_t$. $I[\cdot]$ is a function indicator that takes the values 1 if the residuals are negative and 0 otherwise; $\circ$ denotes the Hadamard product and $\overline{\Xi} = E[\xi_t \xi'_t]$ is the sample covariance matrix of $\xi_t$. A positive value of $g$ implies that past unanticipated bad news ($\eta_{it} < 0$) has a greater impact on future covariance than good news ($\eta_{it} > 0$).

#### 3.3.4. Student's *t*-Copula (*t*-Copula) Model

Copula theory is a relatively new and fast-growing field of research in financial applications. Copula functions have become popular and offer a much greater degree of flexibility to researchers in capturing linear, non-linear and tail dependences of the joint distribution between two or more random variables [83–85]. One of the advantages of copula models over the ADCC model, which is constructed under the assumption of multivariate normality, is that copula models can flexibly model the dependence structure of the two variables through a copula function.

Using the copula method, one can construct a multivariate distribution by specifying first standard uniform marginal distributions and then choosing a copula function that can capture the dependence structure between the variables. Let $X \equiv (x_1, \ldots, x_n)$ be a vector of $n$ univariate variables. If $H$ is denoting the joint $n$-dimensional distribution function and $F_1, \ldots, F_n$ the respective continuous margins of $x_1, \ldots, x_n$, Sklar's theorem states that a function $C$ called copula exists, which joins $F_1, \ldots, F_n$ as follows:

$$H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)) = t_p\left(t^{-1}(u_1), \ldots, t^{-1}(u_1)\right)$$

Equivalently, we can say that given any collection of marginal $F_k$ and any copula $C$, we can use Sklar's theorem to recover the joint distribution from the uniform marginal distributions, $u = (u_1, \ldots, u_n) \in [0,1]^n$, as follows:

$$C(u_1, \ldots, u_n) = \left(F_1^{-1}(u_1), \ldots, F_n^{-1}(u_n)\right)$$

where $F_1^{-1}$ is the generalized inverse of $F_k$.

In this paper, we use Student's $t$-copula ($t$-copula) to study the dynamic dependence structure and capture the extreme co-movement and tail dependence. The $t$-copula is given by:

$$C(u_1, \ldots u_2) = t_p\left(t^{-1}(u_1), \ldots, t^{-1}(u_1)\right)$$

$$= \int_{-\infty}^{t^{-1}(u_1)} \ldots \int_{-\infty}^{t^{-1}(u_1)} \frac{1}{\Gamma\left(\frac{v}{2}\right)(v\pi)^{\frac{n}{2}}|\rho|^{\frac{1}{2}}}\left(1 + \frac{1}{v} z^T p^{-1} z\right)^{-\frac{v+n}{2}} dz_1, \ldots, dz_n$$

The dynamics of $u_1, \ldots, u_n$ are modeled by a GARCH(1,1) process.

### *3.4. Hedging Performance*

For the evaluation of out-of-sample performance of hedging strategies, we split the whole sample into two subsamples and a fixed-length rolling window approach is adopted. The first period is from 3 January 2014, to 28 December 2018 (261 weekly data), which is used to estimate the model parameters. The second period is from 4 January 2019, to 30 June 2023 (235 weekly data), which is used to make a forecast of the optimal hedge for each week and evaluate out-of-sample hedging performance. We first employ weekly returns of five years (261 weekly sets of data) to take an initial estimation of each model's parameters and to obtain the first one-step-ahead forecast of the hedge ratio; then, a window of fixed size rolls over one week ahead, estimating the models and forecasting the hedge ratios again until the end-date. The effectiveness of the hedge ratio for each model is assessed based on two criteria popular in the literature: (a) variance reduction hedging effectiveness [86] and (b) the Diebold–Mariano test [87].

3.4.1. Variance Reduction Hedging Effectiveness (HE)

One of the most widely used criteria for evaluating the hedging effectiveness is the variance reduction hedging effectiveness derived by [86]. Using the HE measurement, the relative performance of different models is evaluated based on the variance of the hedged portfolio returns relative to holding a spot position (unhedged portfolio). Following [86], we evaluate the HE of each model as follows:

$$HE = \frac{var(r_t^u) - var\left(r_t^h\right)}{var(r_t^u)} = 1 - \frac{var\left(r_t^h\right)}{var(r_t^u)}$$

where $var\left(r_t^h\right)$ and $var(r_t^u)$ are defined as the variance of the hedged portfolio and unhedged portfolio, respectively. HE measures the percentage reduction of variance in the hedged portfolio against the unhedged portfolio, whereas a HE of 1 implies a perfect hedge, and a HE of 0 implies no risk reduction.

3.4.2. Diebold–Mariano (DM) Test

Our analysis also uses the Diebold–Mariano test [87] to compare the forecasting performance of the competing models. The statistical significance of apparent predictive superiority of a model over others relies on the loss function, $d_t$, which is defined as follows:

$$d_t = [\updownarrow(e_{m,t}) - \updownarrow(e_{n,t})]$$

where $\updownarrow(\cdot)$ is a function of the forecast errors, $e_{m,t}$ and $e_{n,t}$, of models $m$ and $n$, respectively. In the case of hedging, it is assumed that the function $\updownarrow(\cdot)$ takes the form $(s_t - \lambda_t f_t)^2$ for any given hedging model. The null hypothesis, $H_0$, assumes that the expected losses for two hedging models are equal; that is, $E(d_t) = 0$.

## 4. A Case Study: $CO_2$ Emissions and Bunker Risk Management in Shipping

In this section, we provide a case study where we look at estimating the bunker fuel cost and carbon allowance cost for selected vessel types and voyages and explore the emissions and bunker risk management in shipping. We consider the cases of voyages charter in which the shipowners agree to transport a specified amount of cargo from a designated loading port to a designated discharging port. Under a voyage charter contract, the shipowner is responsible for all expenses incurred during the voyage, including the bunker fuel cost and the carbon allowance cost. In our analysis, we use inputs from the operation of three types of vessels: the Very Large Crude Carrier (VLCC), the Suezmax and Capesize. The first two vessels deliver the largest crude oil volumes in the liquid bulk markets, while the Capesize is employed mainly in the transportation of coal and iron ore. We utilize information provided by Clarksons (for details, please refer to Clarksons' documentation, titled: "Sources & Methods for the Shipping Intelligence Weekly") about the vessels with respect to their fuel consumption and speed in laden and ballast status. The vessels specifications and voyage information are shown in Table 2.

The fronthaul voyage of the VLCC from the departing port of Ras Tanura (Saudi Arabia) to the arrival port of Rotterdam (Netherlands), sailing on an average speed of 12.5 knots lasts approximately 39.5 days. For this voyage, the vessel consumes approximately 2647 tonnes of HSFO. The $CO_2$ emissions for this amount of fuel oil are equal to 8244 tonnes. Given that 50% of emissions apply to ships arriving at an EU/EEA port from a non-EU/EEA port, the emissions under the EU ETS to be considered are 4122 tonnes of $CO_2$. Therefore, the EU ETS compliance cost for this voyage is estimated to be 359,297€, assuming the spot price of EUR 87.17 per tonne of $CO_2$ from the EEX, as of 30 June 2023. The VLCC consumes about 67 tons of fuel daily for a price of EUR 433.5/ton, which represents a fuel cost of USD 1,147,492. The backhaul voyage of the same vessel from the port of Rotterdam to the port of Ras Tanura via the Suez Canal lasts 16.3 days, which translates to the consumption of 2647 tonnes of HSFO and 1296 tonnes of $CO_2$, calculated under the EU ETS requirement for considering 50% of the emitted $CO_2$ of ships departing from an EU/EEA port and heading to a non-EU/EEA port. The EU ETS compliance cost for backhaul voyage is estimated to EUR 112,932. The fuel cost of the backhaul voyage is estimated to EUR 360,671.

**Table 2.** Vessel specifications and voyage assumptions used in the case study.

| | | Voyage 1 | Voyage 2 | Voyage 3 |
|---|---|---|---|---|
| | | | Vessel specifications | |
| Vessel type | | VLCC | Suezmax | Capesize |
| Dwt | | 318,000 | 157,000 | 180,000 |
| Speed (knots) | Laden | 12.5 | 12.5 | 12 |
| | Ballast | 12 | 12 | 13 |
| Consumption at sea (tons/day) | Laden | 67 | 45 | 43 |
| | Ballast | 51 | 35 | 43 |
| | | | Voyage assumptions (at sea) | |
| Trading route | | Ras Tanura–Rotterdam | Houston–Rotterdam | Tubarao–Rotterdam |
| Voyage distance (miles) | Laden | 11,289 | 5041 | 11,289 |
| | Ballast | 4475 | 5041 | 4475 |
| Sea time (days) | | 55.9 | 36.0 | 38.1 |
| | | | Voyage assumptions (in ports) | |
| Port time (days) | | 4 | 4 | 6.5 |
| Consumption in port (tons/day) | | 5 | 5 | 5 |

Notes: This table presents the specifications of three vessel types selected for the case study application of hedging strategies and the respective details on the voyages, which we assume that the shipowners agree to transport cargoes from designated non-EU loading ports to designated EU discharging ports. Data are from Clarksons' documentation, titled "Sources & Methods for the Shipping Intelligence Weekly".

Using the vessel's specifications and the assumption for the other two voyages as presented in Table 2, we conclude that the EU ETS compliance cost for a Suezmax vessel, which is fixed for the round voyage between the port of Houston (USA) and port of Rotterdam (Netherlands), is EUR 195,063.

The last scenario in our case study includes a Capesize vessel that operates between the iron-ore-producing Brazil (the port of Tubarao) and Northern Europe (the port of Rotterdam in the Netherlands), where the steel mills are established. The total carbon allowance cost of the round voyage is estimated to EUR 205,614.

In what follows, we develop the hedging strategies using the alternative econometric model for repeated round voyages over the sample period, assuming that the shipowner's objective is to reduce the risk associated with $CO_2$ allowance prices and bunker fuel prices for multiple voyages over the period from 4 January 2019, to 30 June 2023. To illustrate this process, as presented in Table 3, we consider that the shipowner fixes a voyage charter contract for his vessel on 4 January 2019, for a shipment that will take place one month later. The shipowner wants to be protected against an increase in $CO_2$ allowance price and bunker fuel price in February and has decided to take a long-hedged risk management strategy on $CO_2$ and petroleum futures contracts.

In practice, we use the hedge ratio provided by the econometric models in order to define the size of the futures position relative to the exposure in the $CO_2$ allowance and bunker fuel markets. Then, the one-month-ahead results of hedging effectiveness are assessed through the variance reduction hedging effectiveness and Diebold–Mariano tests. With the completion of this voyage and the evaluation of the different hedging strategies, it follows a period of 15 days before the shipowner fixes the next voyage. The process is repeated until the end-of-sample period.

**Table 3.** Algorithm for hedging the $CO_2$ and bunker fuel prices risk of repeated round voyages.

| Algorithm | Description |
|---|---|
| **Hedging instruments data input (at time t):** $CO_2$ future price, petroleum futures prices | At time $t$, the shipowner fixes a voyage charter contract for a shipment at time $t + n$. To hedge his exposure to the $CO_2$ and bunker cost, he decides to buy the forward $CO_2$ and petroleum hedging instruments contracts in order to lock his $CO_2$ allowance and bunker prices. |
| **Hedge ratios (at time t):** Econometric model estimations for the hedge ratios | The number of future contracts for hedging $CO_2$ and bunker cost for both the fronthaul and backhaul voyages are determined using the results of the hedge ratios that the econometric models have estimated using the market return data over the period from $t - 361$ to $t$ (estimation window). |
| **Hedging effectiveness assessment (at time t + n):** Estimation of the variance reduction hedging effectiveness and Diebold–Mariano tests | The out-of-sample hedging effectiveness is assessed at time $t + n$, comparing the variance of hedged portfolio across the different econometric models, as well as the reduction in the variance of the hedged portfolio relative to the unhedged portfolio. |
| **Voyage completion and idle time before a new voyage will be fixed** | The vessel has returned to the loading ports and is waiting a period of 7 days before a new voyage will be fixed for a shipment that will take place 1 month later. |

Notes: This table outlines the main estimation steps of the algorithm, which has been developed to implement the hedging strategy for the carbon allowance cost and bunker fuel cost of selected voyages between non-EU ports and EU ports subject to EU ETS.

## 5. Data

Our dataset comprises time series of weekly spot and futures prices for EUAs, spanning from 3 January 2008 to 30 June 2023, with 496 observations. In line with the Phases set by policymakers, our study expands into two periods, which are referred to as EU ETS Phase III (2013–2020) and the recent EU ETS Phase IV (2021–2028) (Commencing operation in January 2005, three phases were set out in the EU-ETS: Phase I (2005–2007), Phase II (2008–2012) and Phase III (2013–2020)). We do not include the data from the Phase I and II periods since the EUA are substantially different from the Phase III and IV, and due to regulatory and trade mechanism changes [88]. The spot prices of the carbon allowances are drawn from the European Energy Exchange (EEX), and the carbon futures prices are from the Intercontinental Exchange (ICE). The carbon prices from both exchanges are highly correlated; however, the volume traded on the ICE is significantly higher than the EEX [89]. Although ICE offers futures contracts on EUAs for different maturities, we have used the future contract of one month to mitigate liquidity concerns.

In addition to the EUA market futures and spot prices, we utilize the marine bunker prices of heavy-sulfur fuel oil (HFLSO), represented by HSFO 380 prices ($/ton) at the port of Rotterdam, and several energy futures to examine the hedging effectiveness of bunker cost. The potential hedging instruments for the bunker fuel price risk considered in this study are the future contracts of Brent crude oil (Brent), West Texas Intermediate (WTI) ($/barrel), natural gas (NGas) ($/MMBtu) and refined oil futures such as heating oil (Heat) ($/gallon) and the New York harbor RBOB regular gasoline (RBOB) ($/gallon). Brent is traded at the ICE in London, while all other contracts are traded at the New York Mercantile Exchange in New York (NYMEX). All data used in the empirical analysis, except for the HSFO prices derived from Clarksons Shipping Intelligence Network (SIN), were collected through the Refinitiv Eikon platform. Before proceeding to the empirical analysis, all data expressed in the US Dollar have been converted to Euro using the USD/Euro exchange rates series from the European Central Bank. Figure 1 shows the time series plots of the raw data. Table 4 reports the key descriptive statistics on the log returns. It includes the mean, standard deviation, maximum, minimum, skewness and kurtosis values, the Jarque and Bera statistic [90] and the Phillips–Perron unit root test [91] for stationarity of the series.

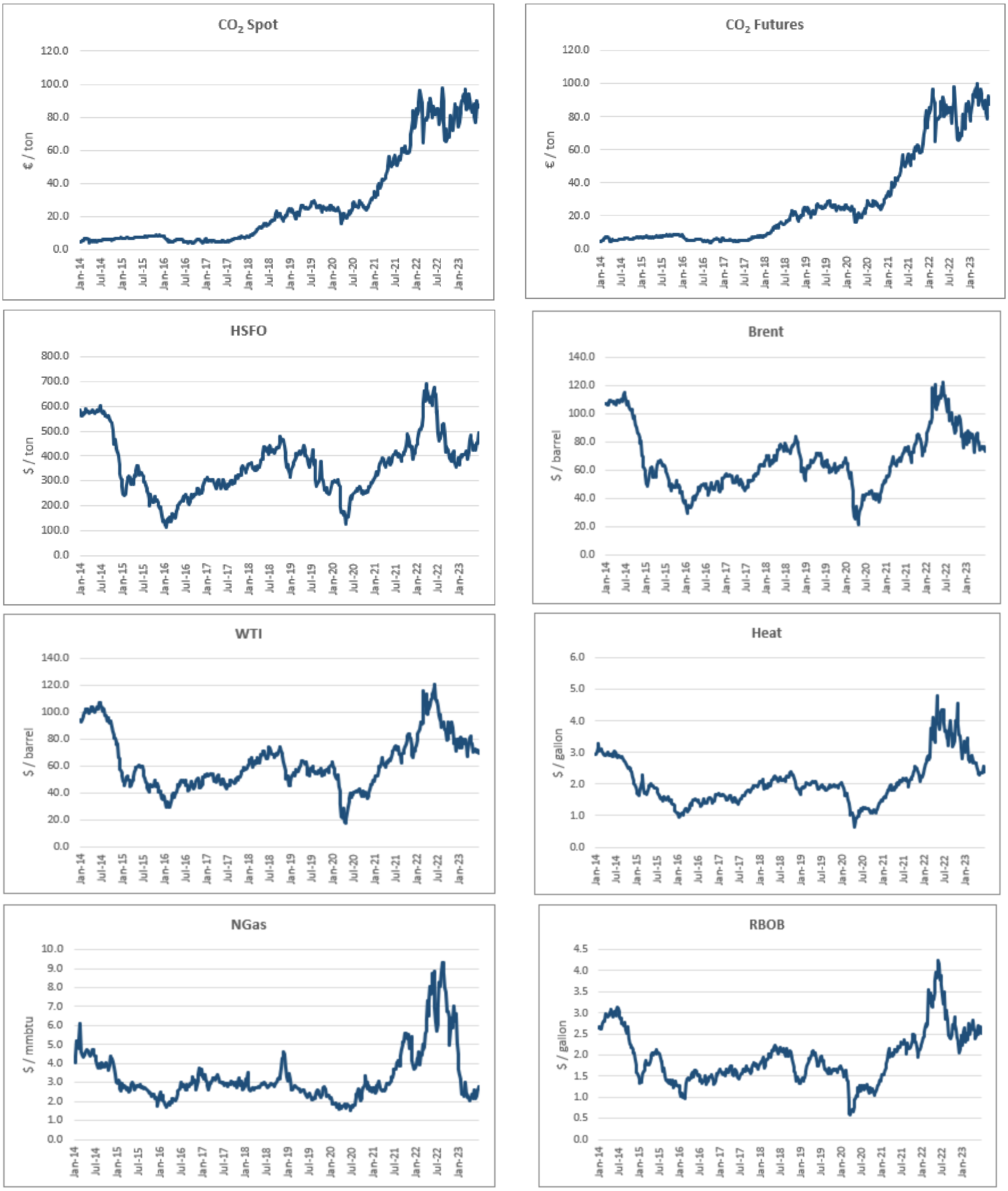


**Figure 1.** Weekly time series plots of spot-futures carbon emission allowance prices, spot bunker fuel prices and petroleum futures prices.

Over the time period studied, the mean value of the return series presented is positive only for the carbon allowance markets. Volatility, as evidenced by the standard deviation ranging from 5.46% to 7.42%, is found to be quite similar over all markets. The sample skewness for all series and most carbon and RBOB markets series is negative, indicating that negative shocks are more common than positive ones in these markets. For all datasets, the excess kurtosis value is high, ranging from 4.341 to 12.538, indicating that the return distributions are leptokurtic, with substantially heavier tails than the normal distribution. The findings of non-zero skewness and high kurtosis support that return series are non-normally distributed and are corroborated by their high and significant Jarque–Bera statistic [90]. The Phillips–Perron test [91] is used to test the null hypothesis of a unit root against the alternative hypothesis of stationarity. The tests result in high negative values, such that return series reject the null hypothesis at the 1% significant level, indicating that return series are stationary.

**Table 4.** Descriptive Statistics.

| | $CO_2$ Spot | $CO_2$ Futures | HSFO | Brent | WTI | Heating | NGas | RBOB |
|---|---|---|---|---|---|---|---|---|
| **Panel A. Price level** | | | | | | | | |
| **Mean** | 28.209 | 28.434 | 361.23 | 67.662 | 62.924 | 2.0763 | 3.3316 | 1.9470 |
| **S.D.** | 28.139 | 28.518 | 120.37 | 21.334 | 20.486 | 0.7356 | 1.4260 | 0.6293 |
| **Max** | 97.580 | 99.800 | 688.75 | 122.01 | 120.67 | 4.7817 | 9.3360 | 4.2522 |
| **Min** | 4.0800 | 4.0800 | 112.00 | 21.440 | 16.940 | 0.6467 | 1.4950 | 0.5737 |
| **Skewness** | 1.1423 | 1.1589 | 0.4339 | 0.5608 | 0.6427 | 0.9967 | 1.8929 | 0.8355 |
| **Kurtosis** | 2.8638 | 2.9123 | 2.7912 | 2.6660 | 2.8307 | 3.8228 | 6.8166 | 3.7266 |
| **J-B** | 108.24 * | 111.18 * | 16.466 * | 28.305 * | 34.735 * | 96.111 * | 597.25 * | 68.617 * |
| **PP test** | 0.8219 | 0.8629 | −0.9284 | −1.0760 | −0.9488 | −0.9001 | −1.1540 | −0.6248 |
| **Panel B: Logarithmic returns** | | | | | | | | |
| **Mean** | 0.0059 | 0.0059 | $-4.413 \times 10^{-4}$ | $-7.184 \times 10^{-4}$ | $-5.763 \times 10^{-4}$ | $-3.694 \times 10^{-4}$ | $-8.699 \times 10^{-4}$ | $-1.131 \times 10^{-5}$ |
| **S.D.** | 0.0653 | 0.0654 | 0.0580 | 0.0546 | 0.0578 | 0.0557 | 0.0742 | 0.0611 |
| **Max** | 0.2427 | 0.2356 | 0.2513 | 0.3135 | 0.2758 | 0.2816 | 0.2184 | 0.2703 |
| **Min** | −0.3495 | −0.3510 | −0.3473 | −0.2907 | −0.3469 | −0.3912 | −0.2860 | −0.4348 |
| **Skewness** | −0.7165 | −0.7236 | −0.5316 | −0.2276 | −0.4483 | −0.5424 | −0.4760 | −0.9383 |
| **Kurtosis** | 6.9247 | 6.8112 | 8.8219 | 8.6431 | 8.3365 | 10.4583 | 4.3414 | 12.5385 |
| **J-B** | 360.04 * | 342.77 * | 722.38 * | 661.07 * | 603.95 * | $1.171 \times 10^3$ * | 55.801 * | $1.949 \times 10^3$ * |
| **PP test** | −22.491 * | −22.541 * | −20.263 * | −20.603 * | −19.035 * | −22.693 * | −22.529 * | −20.404 * |

Notes: This table provides summary statistics and unit root tests for spot and futures returns of carbon emission allowances, bunker and petroleum prices. J-B stands for the Jarque and Bera test [90] for Normality, and PP test is the Phillips–Perron unit root test [91]. * Denotes the rejection of the null hypothesis at a 1% significance level. $CO_2$ Spot is the European Union allowances spot prices; $CO_2$ Futures is the European Union allowances futures prices; Brent is the European crude oil North Sea Brent futures; WTI is the West Texas Intermediate crude oil futures; Heat is the heating oil (No 2) futures; NGas is natural gas futures; and RBOB is the New York harbor RBOB gasoline.

## 6. Estimation Results

### *6.1. Single Hedging Strategy Performance*

In this section, we address the issue of carbon allowance risk hedging by considering the volatility interactions between carbon spot and future markets. The question we are therefore interested in is whether the carbon allowances spot prices can be effectively hedged by the carbon futures contracts traded on the Intercontinental Exchange. In order to address this question, we use four econometric models, the OLS, ECM, ADCC and *t*-copula, to estimate the joint distribution of spot and futures returns and thus estimate the covariance matrix that ultimately determines the hedge ratios. The second issue raised by estimating the OHR through the competing models is whether the most advanced approaches (ADCC and *t*-copula models) outperform the conventional models. To formally compare the out-of-sample performance of each type of hedge, portfolios implied by the computed hedge ratios each week are constructed and the variance of the returns of these portfolios over the sample period are calculated. Moreover, the variance reduction hedge effectiveness, proposed by [86] and the Diebold–Mariano test [87], are also considered in our assessment analysis. The results of the out-of-sample hedging performance for spot $CO_2$ allowance for the period 4 January 2019, to 30 June 2023, are presented in Table 5. All models achieved significant variance reduction in the out-of-sample periods. The variance values for the unhedged portfolios and hedged portfolios of the competing models indicate that the best-performing model is the traditional OLS model, with a variance reduction of 99.4%. The next best-performing models are the ECM and *t*-copula models, which statistically outperform the ADCC model. Although the ADCC shows the lowest variance reduction compared to the other models, in absolute terms, the variance reduction of the hedged portfolio using the ADCC is at the level of 98.2% compared to the variance of the unhedged portfolio. The high correlation between the spot and future carbon allowance markets explains the high degree of hedging effectiveness achieved through the use of both static and dynamic models in this study. In Table 5, we also assess the models providing a pairwise comparison of the predictive accuracy using the standard Diebold–Mariano test. The OLS and ECM hedge strategies outperform the other strategies generated by the ADCC and *t*-copula models. The results of Diebold–Mariano tests reject the null hypothesis that the expected losses of the models are equal. Given the higher score produced by the HE test, we conclude that the OLS and ECM hedge strategies provide superior gains compared to those obtained from the dynamic model.

**Table 5.** Out-of-sample single hedging performance of spot carbon allowances.

| | **Variance** | **HE** | **DM** | | |
|---|---|---|---|---|---|
| | | | **ECM** | **ADCC** | ***t*-Copula** |
| **Unhedged** | 0.4453 | | | | |
| **OLS** | 0.0024 | 99.471 | −0.1598 | −2.6402 *** | −4.3980 *** |
| **EC** | 0.0024 | 99.470 | | −2.6392 *** | −4.4023 *** |
| **ADCC** | 0.0079 | 98.233 | | | 2.0795 ** |
| ***t*-copula** | 0.0035 | 99.212 | | | |

Notes: This table provides the out-of-sample hedging performance of four different models in the carbon allowance market. The out-of-sample period stems from 4 January 2019, to 30 June 2023. Variance of the unhedged and hedged portfolios corresponds to logarithmic returns variance multiplied by 100. Percentage hedging effectiveness for variance reduction (HE) is also presented. We also report the results of the Diebold–Mariano (DM) test; significance at 1% and 5% levels are denoted by *** and **, respectively. OLS denotes the ordinary least square model; ECM is the error correction model; ADCC denotes the asymmetric conditional correlation model; and *t*-copula is the Student's *t*-copula model.

Interestingly, our study does not support the superiority of more sophisticated models, as the conventional OLS is ranked as the best-performing model [70,92]. The GARCH-type strategies, as represented by the ADCC and *t*-copula models, produce higher variance than the OLS and ECM strategies. As noted in the literature, some of the potential explanations for the low hedging effectiveness of the GARCH-type models are [70,72,93]: (i) they have more parameters to estimate and hence higher estimation errors than other models; (ii) model misspecification could also be a potential factor that makes the GARCH-type models perform worse than other models the more parameters; (iii) Allowing for time variation across the variance-covariance matrix of returns, the dynamic models seems to induce greater variance while forming hedged portfolios, and the OHR are more sensitive to the size and sign of the change in prices. It is obvious that the OLS model is more stable and not as volatile as its dynamic counterparts, which is especially useful in hedging strategies where there is a strong correlation between spot and future prices.

### 6.2. Composite Hedging Strategy Performance

In the face of shipping inclusion into EU ETS, it becomes interesting to manage carbon and bunker risks simultaneously with an optimal hedging model. To gain a better understanding of the risk management associated with these two risks, we have developed a composite hedging strategy that uses more than one hedging instrument to offset the risk of two spot positions in carbon allowance and bunker markets. The existence of active carbon futures markets and the high correlation between spot and futures carbon allowances price returns shown in the previous section make the task of hedging easier. In contrast, the fact that there is not a functioning futures market for bunker fuel raises the question, of which futures contract should be used to hedge the bunker risk. In the composite hedge, we evaluate alternative petroleum future contracts (Brent, WTI, heating oil natural gas and RBOB) to hedge the bunker risk. Thus, the present study addresses the possibility of combining carbon and petroleum future contracts to a combination hedging in reducing the joint price risk under study.

For each one of the four econometric models, a forecast was made of the optimal hedge for each week from 4 January 2019 to 30 June 2023. This analysis yields a total of 235 out-of-sample hedge results. Summary statistics of the out-of-sample hedge ratios are presented in Table 6. As can be seen, the hedge ratios vary from model to model. However, the calculated hedge ratios for the two conventional models, OLS and ECM, are very close to each other in all the pairs of hedged instruments used in the study. This is not surprising, given that they share model static regression model fundamentals, our previous findings in the case of single hedging strategies and the empirical results of other studies in the literature [26,72].

**Table 6.** Summary statistics of optimal carbon and petroleum hedge ratios.

| | OLS | | ECM | | ADCC | | *t*-copula | |
|---|---|---|---|---|---|---|---|---|
| **Panel A. Carbon and Brent** | | | | | | | | |
| | **Carbon** | **Brent** | **Carbon** | **Brent** | **Carbon** | **Brent** | **Carbon** | **Brent** |
| **Mean** | 1.0444 | 0.5667 | 1.0218 | 0.5400 | 1.2152 | 0.1503 | 1.0037 | 0.1616 |
| **Variance** | 0.0021 | 0.0037 | 0.0006 | 0.0021 | 0.1294 | 0.0054 | 0.0023 | 0.0158 |
| **Max** | 1.1274 | 0.7044 | 1.0794 | 0.6523 | 2.4910 | 0.3695 | 1.1817 | 0.6858 |
| **Min** | 0.9588 | 0.4883 | 0.9684 | 0.4767 | 0.4519 | 0.0008 | 0.8076 | 0.0009 |
| **Panel B. Carbon and WTI** | | | | | | | | |
| | **OLS** | | **ECM** | | **ADCC** | | ***t*-copula** | |
| | **Carbon** | **WTI** | **Carbon** | **WTI** | **Carbon** | **WTI** | **Carbon** | **WTI** |
| **Mean** | 1.0625 | 0.4579 | 1.0432 | 0.4105 | 1.2355 | 0.1399 | 1.0309 | 0.1324 |
| **Variance** | 0.0024 | 0.0069 | 0.0012 | 0.0058 | 0.1303 | 0.0046 | 0.0021 | 0.0078 |
| **Max** | 1.1428 | 0.6347 | 1.0966 | 0.5721 | 2.5015 | 0.3998 | 1.2110 | 0.5320 |
| **Min** | 0.9687 | 0.3720 | 0.9675 | 0.3439 | 0.4709 | 0.0108 | 0.8201 | 0.0023 |
| **Panel C. Carbon and Heat** | | | | | | | | |
| | **OLS** | | **ECM** | | **ADCC** | | ***t*-copula** | |
| | **Carbon** | **Heat** | **Carbon** | **Heat** | **Carbon** | **Heat** | **Carbon** | **Heat** |
| **Mean** | 1.0677 | 0.6272 | 1.0466 | 0.6340 | 1.2370 | 0.1469 | 1.0271 | 0.1394 |
| **Variance** | 0.0035 | 0.0139 | 0.0021 | 0.0086 | 0.1274 | 0.0067 | 0.0023 | 0.0188 |
| **Max** | 1.1709 | 0.7976 | 1.1325 | 0.7632 | 2.4789 | 0.5692 | 1.1998 | 1.1705 |
| **Min** | 0.9635 | 0.3878 | 0.9599 | 0.4433 | 0.4675 | 0.0000 | 0.8174 | 0.0003 |
| **Panel D. Carbon and NGas** | | | | | | | | |
| | **OLS** | | **ECM** | | **ADCC** | | ***t*-copula** | |
| | **Carbon** | **NGas** | **Carbon** | **NGas** | **Carbon** | **NGas** | **Carbon** | **NGas** |
| **Mean** | 1.1125 | 0.1081 | 1.1120 | 0.1234 | 1.2816 | 0.1349 | 1.0911 | 0.0832 |
| **Variance** | 0.0034 | 0.0008 | 0.0023 | 0.0008 | 0.1387 | 0.0068 | 0.0032 | 0.0091 |
| **Max** | 1.1956 | 0.1676 | 1.1786 | 0.1839 | 2.6309 | 0.7448 | 1.3121 | 0.7164 |
| **Min** | 0.9932 | 0.0570 | 1.0082 | 0.0662 | 0.5130 | 0.0000 | 0.8452 | 0.0002 |
| **Panel D. Carbon and RBOB** | | | | | | | | |
| | **OLS** | | **ECM** | | **ADCC** | | ***t*-copula** | |
| | **Carbon** | **RBOB** | **Carbon** | **RBOB** | **Carbon** | **RBOB** | **Carbon** | **RBOB** |
| **Mean** | 1.0338 | 0.4318 | 1.0126 | 0.4193 | 1.2230 | 0.1235 | 1.0143 | 0.1009 |
| **Variance** | 0.0012 | 0.0006 | 0.0006 | 0.0005 | 0.1306 | 0.0049 | 0.0013 | 0.0054 |
| **Max** | 1.1007 | 0.4954 | 1.0560 | 0.4918 | 2.4758 | 0.4515 | 1.1520 | 0.3363 |
| **Min** | 0.9690 | 0.3924 | 0.9578 | 0.3765 | 0.4649 | 0.000 | 0.8174 | 0.0002 |

Notes: This table documents descriptive statistics of OHR of composite hedging strategies using possible combinations of each pair of carbon futures and petroleum futures. Brent is the European crude oil North Sea Brent futures; WTI is the West Texas Intermediate crude oil futures; Heat is the heating oil (No 2) futures; NGas is natural gas futures; and RBOB is the New York harbor RBOB gasoline. OLS denotes the ordinary least square model; ECM is the error correction model; ADCC denotes the asymmetric conditional correlation model; and *t*-copula is the Student's t-copula model.

Moreover, the results show that the average hedge ratios generated from the conventional methods (OLS and ECM) compared to more sophisticated models (ADCC and *t*-copula), indeed, differ. For example, average hedge ratios for all petroleum futures contracts generated via the ADCC and *t*-copula methodologies are less than the corresponding hedge ratios generated via either the OLS or ECM methods. This implies that the shipowner would purchase fewer futures contracts for hedging the fluctuation risk in bunker prices than would be recommended under the OLS and ECM methodologies. However, the variance estimates of the hedge ratios based on the ADCC and *t*-copula methods are considerably higher than the conventional methods, indicating potentially more expensive hedging strategies because the recommended hedge ratios are constantly changing. In all instances, the OHR have the intuitively correct sign, indicating a long position on future contracts.

It follows the out-of-sample performance of composite hedging strategies in Table 7. A close look at the out-of-sample variances for the unhedged and hedged portfolios does not indicate gains from adopting dynamic hedging strategies. The hedged portfolios generated from the ECM and OLS models have the lowest variance among all the hedging strategies. This indicates that the class of constant models outperforms the time-varying hedging models in terms of variance reduction (see Table 7, Panel A). All models have produced significant variance reduction over the unhedged portfolio across the out-of-sample period, as measured by the hedge effectiveness index (see Table 7; Panel B). The minimum reduction is 54.0% in the composite hedging strategy produced by the ADCC model for carbon + RBOB future contracts, while the largest reduction is 71.1% based on the ECM model for the carbon + Brent future contracts. In particular, the ECM model provides an out-of-sample variance improvement over the unhedged portfolio of around 61.9–71.1%, depending on the selected petroleum future contract for hedging the bunker risk. Next, we provide a pairwise comparison of the predictive accuracy using the Diebold–Mariano test. The results are presented in Table 7, Panel C. The composite hedging strategy is dominated by the OLS and ECM models in almost all petroleum futures contracts used as hedging instruments. Interestingly, we observe that *t*-copula models' performance in the case of composite hedging strategy shows substantial improvement over the respective *t*-copula models used under the single hedging strategies. In contrast, the lowest effectiveness is achieved once ADCC is considered.

A comparison of the composite hedging strategies performance for the pairs of carbon futures and the petroleum futures suggests that the pair carbon + Brent works effectively for hedging the carbon and bunker risks among all other pairs, followed by the carbon + Heating oil and carbon + RBOB gasoline futures when considering the results of the OLS and ECM models. In contrast, carbon + natural gas futures are not generally effective in managing the carbon-bunker price risk exposures. Moving to the ADCC and *t*-copula hedging strategies, the carbon + Brent remains the greatest hedging tool (HE = 55.9% and HE = 63.9% for the ADCC and *t*-copula, respectively). However, the results are mixed across all other pairs of carbon + petroleum futures. Our results are in line with other studies in the literature, which show that Brent is the best hedging tool in comparison to all other petroleum hedging instruments for hedging the bunker risk. For out-of-sample variance reductions using Brent future contracts, [30] reported a percentage variance reduction of up to 43.14% and [93] showed that the variance reduction is almost 51.5%.

Overall, we conclude that the development of composite hedging strategies using carbon and petroleum futures contracts can reduce risk and achieve hedged portfolios with minimal variance. In these composite hedging strategies, we reassure the empirical findings of other studies in the literature, which highlight the benefits of Brent futures contracts in hedging the bunker risk. A high degree of HE can be achieved using a spot-future carbon pair in which a significant reduction in risk is reached either in the single hedging strategies for carbon allowance risk or the composite hedging strategies for both carbon allowance and bunker risk. The HE measured by variance reduction and the DM test reveals that complex dynamic hedging strategies, such as the ADCC and *t*-copula model, do not provide benefits compared to the conventional static approaches, such as the OLS and ECM methods.

**Table 7.** Out-of-sample composite hedging performance of spot carbon allowances and bunkers.

| **Panel A. Variance** | | | | | |
|---|---|---|---|---|---|
| | **Unhedged** | **OLS** | **EC** | **ADCC** | ***t*-Copula** |
| **Carbon + Brent** | 1.0148 | 0.2996 | 0.2926 | 0.4465 | 0.3659 |
| **Carbon + WTI** | | 0.3348 | 0.3286 | 0.4568 | 0.3640 |
| **Carbon + Heating** | | 0.3254 | 0.3355 | 0.4523 | 0.3615 |
| **Carbon + NGas** | | 0.3869 | 0.3857 | 0.5127 | 0.3814 |
| **Carbon + RBOB** | | 0.3127 | 0.3135 | 0.4665 | 0.3693 |
| **Panel B. Hedge effectiveness (HE)** | | | | | |
| | | **OLS** | **EC** | **ADCC** | ***t*-copula** |
| **Carbon + Brent** | | 70.4736 | 71.1625 | 55.9997 | 63.9394 |
| **Carbon + WTI** | | 67.0082 | 67.6192 | 54.9862 | 64.1319 |
| **Carbon + Heating** | | 67.9312 | 66.9398 | 55.4290 | 64.3771 |
| **Carbon + NGas** | | 61.8748 | 61.9937 | 49.4722 | 62.4104 |
| **Carbon + RBOB** | | 69.1805 | 69.1105 | 54.0301 | 63.6047 |
| **Panel C. DM test** | | | | | |
| | | | **EC** | **ADCC** | ***t*-copula** |
| | **OLS** | | 0.6671 | −2.3418 *** | −1.1966 |
| **Carbon + Brent** | **EC** | | | −2.7273 *** | −1.5238 * |
| | **ADCC** | | | | 1.9243 ** |
| | **OLS** | | 0.8218 | −2.3587 *** | −0.6912 |
| **Carbon + WTI** | **EC** | | | −2.7029 *** | −0.9839 |
| | **ADCC** | | | | 2.3083 ** |
| | **OLS** | | −3.0267 *** | −2.2895 ** | −0.9196 |
| **Carbon + Heating** | **EC** | | | −2.1343 ** | −0.6753 |
| | **ADCC** | | | | 2.3150 ** |
| | **OLS** | | 0.6592 | −3.2964 *** | 0.8039 |
| **Carbon + NGas** | **EC** | | | −3.2308 *** | 0.6533 |
| | **ADCC** | | | | 3.2325 *** |
| | **OLS** | | −0.2938 | −3.0501 *** | −1.4213 |
| **Carbon + RBOB** | **EC** | | | −3.0709 *** | −1.4392 |
| | **ADCC** | | | | 2.2526 ** |

Notes: This table details the out-of-sample hedging performance for four competing models in different composite hedging contexts. Variance of the unhedged and hedged portfolios corresponds to logarithmic returns variance multiplied by 100. Percentage hedging effectiveness for variance reduction (HE) is also presented. We also report the results of the Diebold–Mariano (DM) test; significance at 1%, 5% and 10% levels are denoted by ***, ** and *, respectively. Brent is the European crude oil North Sea Brent futures; WTI is the West Texas Intermediate crude oil futures; Heat is the heating oil (No 2) futures; NGas is natural gas futures; and RBOB is the New York harbor RBOB gasoline. OLS denotes the ordinary least square model; ECM is the error correction model; ADCC denotes the asymmetric conditional correlation model; and *t*-copula is the Student's *t*-copula model.

### *6.3. Case Study on Carbon and Bunker Risk Hedging in Shipping*

In this section, we investigate the potential economic benefits realized from implementing hedging strategies for the management of risk arising from fluctuations in carbon allowances prices and bunker prices. To illustrate this, we consider a couple of different vessel types and voyage routes, which include port calls in European ports to investigate the bunker consumption cost and $CO_2$ emissions cost associated with the inclusion of the international shipping sector to EU ETS, and hedging strategies that can eliminate the uncertainty associated with these costs. To illustrate how shipowners can benefit from the hedging strategies, we first calculate cost changes for each one of the repeated voyages between the current hypothetical voyage costs (carbon and bunker costs) using the current carbon allowance prices and bunker prices when voyage agreement between shipowner and charterer is signed and the actual voyage costs of carbon and bunker, used by the vessel in performing the voyage. The cost changes are calculated for both the scenarios of unhedged voyage costs and hedged voyage costs. Table 8 displays the out-of-sample hedging performance for repeated round voyages of the three vessel types under study. We calculate the *Variance* of cost changes and the variance reduction in cost changes achieved through hedging, as measured by the HE index. Moreover, we provide summary statistics of the carbon and bunker costs and the total cost for the repeated voyages. To save space, we only report the results of two models, OLS and *t*-copula, and two composite hedging strategies using the carbon-Brent and carbon-heat pairs.

**Table 8.** Hedging risk of voyage carbon emissions and bunker costs.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Panel A. VLCC—Voyage: Ras Tanura–Rotterdam** | | | | | | | |
| | | **Carbon** | **Bunker** | **Total** | | | |
| **Unhedged voyages** | **Variance** | 2.2175 | 2.43314 | 2.1542 | | | |
| | **Mean** | 271,208 | 1,179,158 | 1,450,367 | | | |
| | **Max** | 496,913 | 2,067,189 | 2,532,195 | | | |
| | **Min** | 110,551 | 710,369 | 851,310 | | | |
| | **Total** | 4,339,333 | 18,866,532 | 23,205,866 | | | |
| | | | **OLS** | | | ***t*-copula** | |
| | | **Carbon** | **Bunker** | **Total** | **Carbon** | **Bunker** | **Total** |
| **Hedged voyages (Carbon + Brent)** | **Variance** | 0.2603 | 1.3513 | 0.9999 | 0.3939 | 2.2920 | 1.5813 |
| | **HE** | 88.260 | 44.462 | 53.580 | 82.236 | 5.7976 | 26.592 |
| | **Mean** | 265,797 | 1,162,924 | 1,428,721 | 255,484 | 1,173,514 | 1,428,998 |
| | **Min** | 508,345 | 2,200,648 | 2,666,039 | 499,873 | 2,087,008 | 2,537,307 |
| | **Max** | 110,837 | 630,828 | 741,665 | 102,207 | 706,124 | 808,330 |
| | **Total** | 4,252,751 | 18,606,786 | 22,859,537 | 4,087,739 | 18,776,223 | 22,863,962 |
| **Hedged voyages (Carbon + Heat)** | **Variance** | 0.4308 | 1.2293 | 0.9381 | 0.4176 | 2.2305 | 1.5637 |
| | **HE** | 80.572 | 49.476 | 56.452 | 81.164 | 8.3268 | 27.409 |
| | **Mean** | 272,977 | 1,169,663 | 1,442,640 | 261,770 | 1,174,997 | 1,436,767 |
| | **Min** | 533,848 | 2,104,226 | 2,591,232 | 515,962 | 2,069,378 | 2,535,162 |
| | **Max** | 113,449 | 626,033 | 739,482 | 108,031 | 705,680 | 813,711 |
| | **Total** | 4,367,633 | 18,714,604 | 23,082,237 | 4,188,314 | 18,799,950 | 22,988,265 |
| **Panel B. Suezmax—Voyage: Houston–Rotterdam** | | | | | | | |
| | | **Carbon** | **Bunker** | **Total** | | | |
| **Unhedged voyages** | **Variance** | 1.7432 | 0.8898 | 0.6700 | | | |
| | **Mean** | 115,967 | 513,349 | 629,317 | | | |
| | **Max** | 209,397 | 902,939 | 1,090,775 | | | |
| | **Min** | 47,495 | 210,995 | 260,340 | | | |
| | **Total** | 2,435,313 | 10,780,337 | 13,215,650 | | | |
| | | **OLS** | ***t*-copula** | | | | |
| | | **Carbon** | **Bunker** | **Carbon** | **Bunker** | **Carbon** | **Bunker** |
| **Hedged voyages (Carbon+ Brent)** | **Variance** | 0.2579 | 0.6244 | 0.4785 | 0.3248 | 0.8442 | 0.5790 |
| | **HE** | 85.200 | 29.829 | 28.588 | 81.364 | 5.1347 | 13.5785 |
| | **Mean** | 114,507 | 507,677 | 622,184 | 109,786 | 512,509 | 622,295 |
| | **Min** | 220,527 | 935,925 | 1,097,048 | 209,484 | 914,616 | 1,080,941 |
| | **Max** | 45,908 | 237,436 | 286,932 | 45,609 | 212,027 | 261,164 |
| | **Total** | 2,404,649 | 10,661,211 | 13,065,860 | 2,305,499 | 10,762,691 | 13,068,190 |
| **Hedged voyages (Carbon + Heat)** | **Variance** | 0.4235 | 0.9722 | 0.7206 | 0.3224 | 0.7758 | 0.5279 |
| | **HE** | 75.7020 | 0.000 | 0.000 | 81.5032 | 12.8159 | 21.215 |
| | **Mean** | 117,565 | 504,046 | 621,610 | 112,096 | 513,183 | 625,279 |
| | **Min** | 229,205 | 947,781 | 1,111,963 | 212,113 | 917,521 | 1,095,771 |
| | **Max** | 46,094 | 223,326 | 273,580 | 46,259 | 226,961 | 277,405 |
| | **Total** | 2,468,857 | 10,584,962 | 13,053,819 | 2,354,016 | 10,776,838 | 13,130,854 |

**Table 8.** *Cont.*

| **Panel C. Capesize—Voyage: Tubarao–Rotterdam** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Carbon** | **Bunker** | **Total** | | | |
| **Unhedged voyages** | **Variance** | 1.7432 | 0.8898 | 0.6700 | | | |
| | **Mean** | 115,967 | 513,349 | 629,317 | | | |
| | **Max** | 209,397 | 902,939 | 1,090,775 | | | |
| | **Min** | 47,495 | 210,995 | 260,340 | | | |
| | **Total** | 2,435,313 | 10,780,337 | 13,215,650 | | | |
| | | **OLS** | ***t*-copula** | | | | |
| | | **Carbon** | **Bunker** | **Carbon** | **Bunker** | **Carbon** | **Bunker** |
| **Hedged voyages (Carbon+ Brent)** | **Variance** | 0.2579 | 0.6244 | 0.4785 | 0.3248 | 0.8442 | 0.5790 |
| | **HE** | 85.200 | 29.829 | 28.588 | 81.364 | 5.1347 | 13.5785 |
| | **Mean** | 114,507 | 507,677 | 622,184 | 109,786 | 512,509 | 622,295 |
| | **Min** | 220,527 | 935,925 | 1,097,048 | 209,484 | 914,616 | 1,080,941 |
| | **Max** | 45,908 | 237,436 | 286,932 | 45,609 | 212,027 | 261,164 |
| | **Total** | 2,404,649 | 10,661,211 | 13,065,860 | 2,305,499 | 10,762,691 | 13,068,190 |
| **Hedged voyages (Carbon + Heat)** | **Variance** | 0.4235 | 0.9722 | 0.7206 | 0.3224 | 0.7758 | 0.5279 |
| | **HE** | 75.7020 | 0.000 | 0.000 | 81.5032 | 12.8159 | 21.215 |
| | **Mean** | 117,565 | 504,046 | 621,610 | 112,096 | 513,183 | 625,279 |
| | **Min** | 229,205 | 947,781 | 1,111,963 | 212,113 | 917,521 | 1,095,771 |
| | **Max** | 46,094 | 223,326 | 273,580 | 46,259 | 226,961 | 277,405 |
| | **Total** | 2,468,857 | 10,584,962 | 13,053,819 | 2,354,016 | 10,776,838 | 13,130,854 |

In panel A of Table 8, we present the out-of-sample hedging performance of 16 round voyages performed by a VLCC vessel from the port of Ras Tanura (Saudi Arabia) to the arrival port of Rotterdam (Netherlands). A comparison of the variance reductions reveals that the out-of-sample HE is higher when the OLS model is applied, and the selected hedging instruments are carbon-Brent. For instance, in the case of the carbon-Brent pair, the variance reduction is 88.2% for the carbon cost, assuming use of the OLS model, whereas the same hedging model and hedging instruments yield a variance reduction of 44.4% for the bunker cost. Although the purpose of a hedging strategy implementation is to remove all uncertainty associated with carbon and bunker risk, the results also indicate small economic gains by means of total cost reduction for the hedged positions compared to the unhedged positions. Specifically, the total unhedged voyage cost for 16 round voyages of the VLCC vessel is EUR 23.20 million, while the total hedged voyage costs using the pairs carbon-Brent and carbon-heat hedging instruments are EUR 22.86 million and EUR 23.08 million. In percentage terms, the cost reductions achieved through the hedging strategies using the OLS model are 1.49% and 0.53%, respectively.

In panels B and C of Table 8, we present the results of out-of-sample hedging performance of 21 round voyages for the vessels of Suezmax (from the port of Houston (US) to the port of Rotterdam (Netherlands)) and Capisize (from the port of Tubarao (Brazil) to arrival port of Rotterdam (Netherlands)), respectively. The findings of HE from the hedging strategies applied to these voyages are similar to hedging effectiveness and variance reduction in voyage costs of the VLCC vessel. Results confirm the robustness of the OLS hedging strategy compared to the more complex *t*-copula hedging strategy.

## 7. Conclusions

In this article, we have investigated the hedging effectiveness of carbon and petroleum futures contracts in managing the risk of carbon and bunker prices, respectively, providing some useful insights and implications in the shipping industry. The study is both important and timely after the formal adoption of a new EU maritime regulation [94] in July 2023 for the integration of maritime transport into EU ETS. To be specific, shipping companies would be required to surrender $CO_2$ allowances to cover their emissions from voyages between ports within the EU, as well as emissions from all inbound and outbound voyages between the EU and non-EU ports. Therefore, the inclusion of shipping into the EU ETS introduces a new major risk in the shipping industry, that is, carbon risk, and makes the development of carbon risk management a high priority for shipping companies.

Our study evaluates the performance of hedging strategies in the carbon and bunker markets using alternative econometric models to estimate the OHR. Out-of-sample comparisons of the hedging effectiveness of strategies based on two traditional models, such as the OLS and ECM, and two sophisticated approaches, ADCC and *t*-copula models, deepen our understanding of the hedge activities, models' performance, and effectiveness of futures contracts as hedging instruments. We initially examine the performance of a single instrument hedging strategy on carbon allowance prices. It follows the development of a composite cross-hedge-setting in which the composite instrument based on the carbon futures contracts and petroleum futures contracts are used for hedging both risk exposure in carbon and bunker markets. Our empirical analysis also includes a case study with the estimation of bunker fuel cost and carbon allowance cost, as well as the practical implementation of hedging strategies for indicative three cargo ship voyages.

Our findings are summarized as follows. First, the results show that the carbon futures contract is a highly efficient hedging instrument for managing the carbon price risk. Our empirical findings indicate that the uncertainty regarding the carbon allowance price changes can be reduced by more than 95%. Second, we investigate whether hedging strategies relying on more sophisticated and complex models generate better hedging strategies than the conventional models in terms of variance reduction hedging effectiveness. The out-of-sample evaluation, based on the variance reduction of hedged portfolios generated via the four competing models, indicates the superior performance of the simplest models. The results show the significant advantage of using the standard OLS and ECM models over the ADCC and *t*-copula models for hedging the carbon risk under the single instrument hedging strategy and both carbon and bunker risk under the composite hedging strategy. Third, Brent futures contracts significantly dominate other petroleum contracts for hedging the bunker price risk. Fourth, we conclude that the spot-future carbon pair is able to offer a high degree of hedging effectiveness to either single instrument hedging strategies for managing only the carbon allowance risk or composite hedging strategies for managing both carbon allowance and bunker risk. Fifth, our article undertakes a case study to provide a practical application of the proposed hedging strategies for managing the carbon and bunker risk of selected voyages and standard vessel types. Our results indicate a variance reduction of estimated voyage costs and economic gains by means of cost reduction for the hedged positions compared to the unhedged positions.

There are some limitations to our study. First, we examine the effectiveness of hedging strategies on bunker risk using spot prices of Rotterdam-delivered bunker fuel. The inclusion of bunker fuel prices from other important bunker hubs (i.e., ports of Houston and Singapore) might provide more empirical findings; however, it would have lengthened the paper further. Second, we focus only on the hedging of bunker risk using bunker prices of heavy-sulfur fuel oil (HFLSO), represented by HSFO 380 prices, which is the cheaper and most commonly used fuel by vessels. However, low-heavy fuel oil and alternative fuels, such as LNG, can also be an option. Another limitation of our study is that we use information about benchmark vessels and selected trading routes for the purpose of estimating fuel consumption and corresponding $CO_2$ emissions in our case study. Despite the stated limitations, our paper contributes to the recent emerging literature that examines the risk management of carbon allowance risk in the shipping industry, and these limitations can be considered as a direction for future research.

The empirical findings of our research are of general interest to market participants and academics in the shipping industry, as well as investors with an interest in risk management around the carbon markets. We propose a hedging framework for managing carbon allowances price risk that can strengthen and expand the scope of existing risk management of shipping companies, which focuses on managing the bunker and freight rates risk. A nice feature of our work is that we present the carbon emissions cost calculation in connection with the bunker fuel consumption and develop our hedging methodology using a composite hedging strategy that involves both the carbon and bunker risk, with the latter being a familiar risk to practitioners in the shipping industry. Moreover, the success of the proposed methods for the estimation of OHR and the high degree of hedging effectiveness indicate potential economic gains by means of stabilized cash flows for shipping companies, thanks to the uncertainty of reduced carbon and bunker fuel prices.

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## Abbreviations

| | |
|---|---|
| ADCC | Asymmetric Dynamic Conditional Correlation |
| CCER | China-certified emissions reduction |
| CCX | Chicago climate exchange |
| CER | Certified emissions reduction |
| CET | Carbon emissions trading |
| $CH_4$ | Methane |
| CII | Carbon intensity indicator |
| $CO_2$ | Carbon dioxide |
| DM | Diebold–Mariano test |
| DWT | Deadweight tonnage |
| EC | European Commission |
| ECM | Error correction model |
| EEA | European economic area |
| EEDI | Energy efficiency design index |
| EEXI | Energy efficiency existing ship index |
| EU | European Union |
| EU ETS | EU emissions trading scheme |
| EUA | European Union Allowances |
| GDP | Gross domestic product |
| GHG | Global greenhouse gas |
| GT | Gross tonnage |
| HE | Hedging effectiveness |
| HFLSO | Heavy-sulfur fuel oil |
| HFO | Heavy fuel oil |
| IMO | International Maritime Organization |
| JVETS | Japan voluntary emissions trading system |
| LNG | Liquified natural gas |
| MBM | Market-based measure |
| MDO | Marine diesel oil |
| MRV | Monitoring, reporting and verification |
| $N_2O$ | Nitrous oxides |
| OHR | Optimal hedging ratios |
| OLS | Ordinary least square |
| RoPax | Roll-On/Roll-Off/Passenger |
| RoRo | Roll-on/Roll-off |
| *t*-copula | Student's *t*-copula |
| VLCC | Very large crude carrier |

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