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Hedging shipping freight rates using conditional Value-at-Risk and Buffered Probability of Exceedance

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ABSTRACT

This paper investigates the performance of the minimum Conditional Value-at-Risk (CVaR) hedging technique in the dry bulk shipping freight market, where extreme volatility and asymmetric return distributions often limit the effectiveness of traditional minimum variance approaches. The CVaR-based framework is used to minimize the downside tail risk in both static and dynamic hedging settings using a dataset of Forward Freight Agreements (FFAs) for Capesize, Panamax and Supramax vessels over the period of January 2007 to December 2022. Our results suggest that the effectiveness of alternative hedging strategies is sensitive to the distributional shape of the underlying returns, underscoring the suitability of CVaR-based strategies under heavy-tailed and skewed returns. Furthermore, we introduce a probabilistic optimization framework that minimizes the Buffered Probability of Exceedance (bPOE), subject to a pre-specified CVaR constraint. This dual-risk formulation yields an efficient frontier, i.e., a set of optimal solutions between risk and return, that quantifies the trade-off between the likelihood and magnitude of extreme losses, ultimately enhancing hedging performance and offering insights into tail risk management.

1. Introduction

The shipping industry provides transportation services for manufactured goods as well as commodities and raw materials including petroleum products, iron ore, coal, minerals, agricultural products, fertilizers and other minor bulk cargoes (Stopford, 2009). In 2024 alone, more than 5.74 billion tonnes of dry cargo were transported by dry bulk vessels worldwide, accounting for approximately 45.4 % of total world seaborne trade.[1] The dry bulk shipping market operates under near-perfect competition, where freight rates are determined by the interaction between supply and demand schedules at any given time. On the demand side, fluctuations in world economic activity, international trade, and demand for raw materials, among other factors, influence freight rates, while on the supply side, fleet size, productivity and port congestion play a significant role (Stopford, 2009). These dynamics, combined with the fact that shipping services cannot be stored, have led to extreme fluctuations in freight rates across shipping sectors, particularly dry bulk carriers. These factors have caused frequent boom and bust cycles and significant volatility in the freight market compared to commodities or financial markets.

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[1] The trades in dry bulk commodities are reported by Clarkson's Shipping Intelligence Network (SIN).

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Fluctuations in the dry bulk market repeatedly manifested in extreme historical episodes when freight rates reached unprecedented levels notably prior to the 2008 financial crisis and amid the COVID-19 pandemic. For example, the Baltic Panamax Index (BPI) doubled (from $30,000/day to $60,000/day) between June and December 2007, only to collapse by over 95 % (from $70,000/day to $3500/day) between May 2008 and December 2008. Such extreme movements in freight rates have drawn considerable attention from researchers and many studies, including Kavussanos (1996), Alizadeh and Nomikos (2009), Tsouknidis (2016), and Yang et al. (2022), document and compare freight rate risk across different shipping sectors and segments using a variety of statistical techniques.

The pronounced volatility in dry bulk freight rates has prompted the development and adoption of various methods and instruments by market participants (traders, ship owners, charterers, operators and investors) to manage freight rate risk effectively. For instance, spot freight rate exposure can be mitigated using period time-charters (TC) or contracts of affreightment (CoA) in the physical market or hedged with Forward Freight Agreements (FFAs) and freight options in the derivative markets. Amongst these risk management instruments, FFAs have gained widespread use in recent years due to their liquidity, flexibility and relatively lower transaction costs (Alizadeh and Nomikos, 2009). FFAs are cash-settled contracts between two parties (a buyer and a seller) to settle the freight rate for hiring a vessel or transporting certain quantities of cargo along major shipping routes, at a predetermined future date, known as the contract's maturity.[2] While the primary function of FFA contracts is to manage freight rate risk, they are also employed by non-shipping entities for speculative purposes or as diversification instruments within broader investment portfolios.[3] The effectiveness of FFA contracts for hedging and risk management, however, depends crucially on the models used to determine hedge ratios.

A large body of literature has therefore evaluated hedging strategies involving freight futures and FFAs in the dry bulk and tanker markets. Among these strategies, the most widely used approach is to estimate the minimum variance hedge ratio (MVHR) which seeks to reduce the overall volatility of a hedged portfolio. However, due to the inelastic nature of shipping supply and sudden demand shocks, conventional models like MVHR and even dynamic approaches such as Bivariate-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) often show limited effectiveness. For instance, Kavussanos and Visvikis (2010) and Alizadeh et al. (2015) find that even advanced econometric models fail to achieve consistently high hedging performance in such volatile environments.

Beyond structural limitations, spot and FFA returns in dry bulk markets are notably skewed and leptokurtic, posing challenges for models that rely on normality. Nomikos et al. (2013) report that logarithmic freight rate returns in these markets display fat tails, driven by extreme fluctuations in supply and demand factors. Such features undermine variance-based hedging, particularly when investors deviate from quadratic utility assumptions or when return distributions are non-normal (Cao et al., 2010). Further, MVHR estimation techniques treat gains and losses symmetrically, which can result in suboptimal risk management strategies, especially in markets with pronounced asymmetries in return distributions. In such cases, variance-based methods may fail to provide adequate protection, particularly for directional exposures, whether long or short. Recent empirical evidence has also shown that the MVHR performs poorly when structural dislocations—such as non-convergence between spot and futures—arise, further questioning its robustness across different market regimes (Goswami et al., 2023).

To overcome these shortcomings, an alternative risk measure and hedging approach known as Conditional Value-at-Risk[4] (CVaR) is proposed by Rockafellar and Uryasev (2000, 2002). CVaR is a quantile-based downside risk metric that explicitly accounts for the non-elliptical nature of return distributions, a feature particularly relevant in hedging applications. Unlike Value-at-Risk (VaR), which captures only the threshold of extreme losses, CVaR considers the magnitude of expected loss beyond the VaR level, thus providing a more comprehensive assessment of tail risk (Cao et al., 2010).

In this paper, we employ the flexible non-parametric CVaR framework to determine the optimal hedge ratio for managing freight rate risk using FFAs, across multiple dry bulk carrier sizes. This approach does not rely on distributional assumptions, making it particularly well-suited for heavy-tailed freight return data. We also extend the static CVaR into a time-varying framework using a rolling window methodology. The performance of CVaR-based hedging strategies is benchmarked against several traditional approaches, including the MVHR (estimated via Ordinary Least Squares), naïve strategies, and time-varying models such as Markov Regime Switching and Bivariate Constant Conditional Correlation GARCH. We evaluate CVaR hedge ratios for both long and short positions across various confidence levels, capturing the impact of risk preferences on the expected downside risk. In addition, we analyze the statistical properties of the hedged portfolio return distributions. We find that differences across strategies are most pronounced in the presence of heavy tails, while they diminish when distributions are approximately normal (Sarykalin et al., 2008).

This study extends the existing literature in five distinct ways that advance both theoretical understanding and practical implementation of freight rate hedging. First, we introduce a CVaR hedging strategy based on expected downside risk that directly minimizes tail losses in managing dry bulk freight rate risk. This provides a downside-focused, risk-aware alternative to traditional variance-minimizing approaches. Second, distributional asymmetries are explicitly incorporated, allowing for different hedge ratios for long and short positions — unlike MVHR and time-varying models that assume symmetry. Third, we compare the in-sample and out-of-sample performance of CVaR-based strategies against benchmarks such as OLS-based, GARCH and Markov Regime Switching

[2] The underlying indices for dry bulk FFA contracts are based on spot market assessments of individual dry bulk routes and baskets of routes published daily by the Baltic Exchange for Capesize (BCI), Panamax (BPI), Supramax (BSI) and Handysize (BHSI) vessels. Similarly, for tanker FFAs, the indices are derived from spot freight assessments for both dirty and clean tankers routes, also published by the Baltic exchange. In the container sector, FFA contracts are based on spot assessments for twelve main container routes, as published by Freightos and the Baltic Exchange.

[3] Discussion and analyses of shipping freight derivatives and markets can be found in Alizadeh and Nomikos (2009).

[4] Conditional Value-at-Risk (CVaR), also known as expected tail loss (ETL) or expected shortfall (ES) is an alternative to Value-at-Risk representing a measure for downside risk based on the expected size of extreme losses of an asset or a portfolio. It is calculated as probability weighted average of the losses on the tail of the distribution of an asset price or portfolio, given certain probability and time horizon.

models. Our evaluation considers not only the variance of the hedged portfolio returns, but also the average return, VaR deviation, mean absolute deviation, standard deviation, and CVaR deviation. Fourth, we implement a time-varying minimum CVaR hedging approach across different confidence levels to reflect varying investor risk preferences.

Furthermore, building on the CVaR-based hedging literature (e.g., Cao et al., 2010; Melnikov and Smirnov, 2012), we utilize a probabilistic optimization framework that incorporates the Buffered Probability of Exceedance (bPOE)[5] for hedging shipping freight rates. While existing CVaR-based approaches aim to minimize the expected size of extreme losses, they do not directly control the probability of breaching a given loss threshold. The bPOE optimization complements CVaR by explicitly addressing this probabilistic dimension of risk. To our knowledge, this is the first study in the shipping freight derivatives and commodity hedging literature to optimize CVaR and bPOE. This yields an efficient frontier that quantifies the trade-off between the probability and magnitude of tail losses, providing a novel probabilistic lens for interpreting tail risk and hedging performance. The growing adoption of probabilistic approaches in freight markets—both in risk management and operational contexts—highlights the need for flexible models that can address distributional uncertainty (Sel and Minner, 2025). The resulting framework offers a practical and robust tool for managing shipping freight rate risk in markets characterized by extreme movements, asymmetric return distributions, and regime shifts.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the applied methodology. Section 4 presents the data and preliminary analysis. Section 5 discusses the main empirical results, and Section 6 concludes.

2. Literature review

The objective of hedging a cash or spot position using derivative instruments is to mitigate the risk of adverse price movements by taking an offsetting position in futures or forward contracts. The theoretical foundation for such hedging strategies was developed by Johnson (1960) and Stein (1961) with Ederington (1979) formalizing the concept of minimum variance hedge ratio (MVHR). MVHR minimizes the total variance of the hedged portfolio by determining the optimal proportion of futures contracts relative to the spot position. Mathematically, it is defined as the ratio of the covariance between spot and futures returns to the variance of the futures returns—equivalent to the slope coefficient in an Ordinary Least Squares (OLS) regression of spot returns on futures returns. This framework serves as a benchmark for evaluating hedge effectiveness across asset classes.

Although widely applied, MVHR strategies face several well-documented limitations in shipping markets. These include poor performance when compared to other dynamic specifications such as GARCH and Regime Switching models and are ineffective under extreme volatility, asymmetries, and fat-tailed return distributions (see Kavussanos and Nomikos, 2000; Alizadeh et al., 2015; Melnikov & Smirnov, 2012; Cao et al., 2010)."

Several studies focus on estimating dynamic hedge ratios, allowing for time variation in the covariance and variances of spot and futures prices using Generalized Autoregressive Heteroscedasticity (GARCH) type models, e.g., Kroner and Sultan (1993), Kavussanos and Nomikos (2000), Alizadeh et al. (2015). These models rely on the conditional variance and covariance of spot and futures price returns to derive dynamic hedge ratios. While such models have shown satisfactory performance in financial and commodity markets, their success in maritime freight markets has been comparatively limited; see, among others, Kavussanos and Nomikos (2000) and Kavussanos and Visvikis (2004). For example, Kavussanos and Visvikis (2010) find that minimum variance hedging in dry bulk markets yields only a 40 % reduction in variance, compared to reductions exceeding 90 % in commodity and financial markets.

To improve hedging effectiveness, some researchers have extended the GARCH-family models to Markov Regime Switching GARCH (MRS-GARCH) frameworks, which allow for both time-varying covariance matrix and structural shifts in the hedge ratio estimation. For instance, Alizadeh et al. (2015) apply this methodology to the tanker market to investigate the performance of FFA hedging. Results show marginal improvement in hedging effectiveness. Overall, the performance of FFAs in hedging physical freight rates using MVHR and time-varying hedge ratios has been weak in both dry bulk and tanker market segments. One explanation for the underperformance of dynamic hedging strategies may lie in the structure and dynamics of the FFA market itself. Despite their broad adoption, FFAs exhibit uneven liquidity across vessel classes, contract maturities, and trading routes.[6] During periods of market stress or low activity, bid-ask spreads widen, order book depth diminishes, and price discovery becomes less efficient. These conditions compromise the estimation and execution of optimal hedge ratios (Alizadeh and Nomikos, 2009). Another reason could be the dynamics and behavior of spot and forward freight rates in terms of extreme volatility, asymmetric distributions, and the presence of jumps, which weaken the stability of spot-forward correlations, further reducing the effectiveness of conventional hedging strategies.

While constant and time-varying minimum variance hedging strategies can effectively reduce the variance of hedged portfolio, they suffer from limitations that are particularly relevant in markets with extreme behavior. A major limitation is the symmetric treatment of losses and gains of the hedged portfolio, equally penalizing both (Melnikov and Smirnov, 2012). In addition, when portfolio returns exhibit excessive tail risk, as reflected by higher order moments such as skewness and kurtosis, minimum variance hedging strategies may not be appropriate or efficient (Cao et al., 2010). In such cases, the optimal hedging strategy should minimize

[5] The Buffered Probability of Exceedance (bPOE) is a measure of risk of an asset or a portfolio representing the likelihood of breaching a specified loss threshold. It is used in conjunction with VaR or CVaR to assess the probability of returns breaching the VaR or CVaR (Rockefeller and Ursayev, 2019). See section 3.2 for further detail.

[6] For instance, Alizadeh and Nomikos (2009) note that FFA trading activity is concentrated in Capesize and Panamax contracts, particularly on basket of trip-charters routes, while smaller vessel classes attract much less liquidity. They also highlight that trading volumes are highest at short maturities, with liquidity thinning considerably for longer-dated contracts.

downside or tail risk, rather than total variance. Several techniques and methods have been developed over the years to assess and manage tail risk, including Value-at-Risk (VaR) and Conditional-VaR (CVaR), which have become standard tools in modern risk management and portfolio optimization.

Rockafellar and Uryasev (2000) introduced CVaR as a more robust alternative to VaR, based on favorable mathematical properties such as stability and ease of estimation or optimization. CVaR measures the expected loss conditional on losses exceeding the VaR threshold and offers continuity with respect to the confidence level. While VaR optimization becomes problematic under non-normal return distributions, CVaR retains computational tractability and reliability, which make it superior to VaR. CVaR is a coherent risk measure which forms a convex objective function that facilitates numerical optimization (Sarykalin et al., 2008; Rockafellar and Uryasev, 2013); satisfying subadditivity, monotonicity, translation invariance, and positive homogeneity. This robustness is particularly important in commodity market applications, where data irregularities and tail events can undermine traditional risk measures (Byers et al., 2021). In financial markets, CVaR has been widely applied in portfolio optimization (Krokhmal et al., 2002) and robust hedging under model uncertainty (Melnikov and Smirnov, 2012). However, despite its theoretical advantages, CVaR has rarely been applied to hedging strategies in commodities and shipping freight markets. Moreover, the integration of probabilistic risk metrics like bPOE has not yet been fully explored. This represents a notable gap in the literature, especially given the asymmetries and heavy tails commonly observed in shipping freight return distributions.

The literature exploring VaR and CVaR-based hedging strategies provides strong evidence of their potential advantages over conventional MVHRs. Harris and Shen (2006) investigate minimum VaR and CVaR hedging strategies using a non-parametric historical simulation method. They conclude that VaR and CVaR hedging approaches outperform traditional minimum variance approaches. Cao et al. (2010) propose a semi-parametric approach for estimating minimum VaR and CVaR hedge ratios, demonstrating significant reductions in tail risk. Similarly, Albrecht et al. (2012) derive analytical hedge ratios under elliptical and mixed elliptical distributions, supporting the superior performance of VaR and CVaR based hedging strategies in out-of-sample tests. Melnikov and Smirnov (2012) develop an optimal hedging strategy semi-explicitly based on CVaR for both financial and insurance applications. These studies suggest that CVaR-based hedging should theoretically outperform MVHR due to the super quantile function used in optimization, which more accurately incorporates asymmetries and tail behavior in return distributions.

Moreover, when optimizing the tail risk of a portfolio, the Buffered Probability of Exceedance (bPOE) offers an intuitive approach to modeling tail risk. Mathematically it is defined as one minus the confidence level at which the CVaR equals some identified value; bPOE allows for direct probabilistic interpretation of tail risk (Rockafellar and Royset, 2010). While CVaR quantifies the expected loss beyond a threshold, bPOE captures the probability of exceeding a given loss level. Together, they enable a dual view, measuring both severity and frequency of tail events. Davis and Uryasev (2016) apply this framework to model tropical storm damage losses, while Shang et al. (2016) extend it to bond immunization, finding that although CVaR and bPOE constraints are equivalent, their optimization results can differ significantly.

Norton et al. (2017) show that minimizing bPOE is equivalent to solving a soft-margin Support Vector Machine (SVM) classification problem under robust optimization. Mafusalov et al. (2018) investigate the convergence rates and asymptotic properties of empirical bPOE estimates, finding that while bias remains low, asymptotic variance can be large under heavy-tailed distributions. This highlights the importance of precision in modeling extreme risk, especially when distributions exhibit fat tails.

While prior studies have examined hedging shipping freight rate risk using FFAs and different time-varying hedging methods, there remains a clear gap in addressing extreme tail losses, non-normal return distributions, and distributional asymmetries in the context of hedge ratio estimation. This paper seeks to address these shortcomings by applying a CVaR-based framework and incorporating Buffered Probability of Exceedance (bPOE) to enhance hedging effectiveness in dry bulk shipping markets. This analysis underscores the need for a tail-focused, distribution-sensitive hedging framework in shipping.

3. Methodology

Shipowners and charterers have been using Forward Freight Agreements (FFAs) to hedge their physical exposure in freight markets since early 2000s. Hedging is typically achieved by taking a position in the FFA market opposite to the physical exposure, thereby creating a hedged freight portfolio with reduced volatility compared to an unhedged position.

Let $R_{s,t}$ and $R_{f,t}$ be the log returns of spot and futures (FFAs) at time *t*, respectively, and h_t represents the hedge ratio at time *t*. The hedged portfolio return at time, $t+1$, is defined as follows:

- Short hedge (protecting a long physical position): $R_{h,t+1} = R_{s,t+1} - h_t R_{f,t+1}$
- Long hedge (protecting a short physical position): $R_{h,t+1} = -R_{s,t+1} + h_t R_{f,t+1}$

In both cases, a negative value of $R_{h,t+1}$ represents a loss, while a positive value indicates a gain. When risk is measured using variance, this symmetric treatment fails to distinguish between gains and losses. Accordingly, the variance of the hedged portfolio return at time $t+1$ is specified as:

$$var(R_{h,t+1}|\Omega_t) = var(R_{s,t+1}|\Omega_t) + h_t^2 var(R_{f,t+1}|\Omega_t) - 2h_t cov(R_{s,t+1}, R_{f,t+1}|\Omega_t) \tag{1}$$

Intuitively, this expression captures the overall risk of the hedged position, treating gains and losses symmetrically. According to Ederington (1979), the minimum variance hedging ratio (MVHR) minimizes the variance of this hedged portfolio return at time *t*, and is given by:

$$h_t^* = \frac{cov(R_{s,t+1}, R_{f,t+1})}{var(R_{f,t+1})} \tag{2}$$

This ratio balances spot and futures positions to minimize portfolio volatility, serving as the standard benchmark for hedging. The MVHR framework can be extended to a time-varying setting by allowing the variance and covariance of spot and FFAs returns, $var(R_{f,t})$ and $cov(R_{s,t}, R_{f,t})$, to evolve over time. This is achieved using dynamic models such as rolling window OLS, Bivariate GARCH, or Regime-Switching GARCH. Both rolling OLS and Bivariate GARCH models allow the estimation of conditional second moments of returns series, adapting the hedge ratio over time. Several studies have employed different multivariate GARCH specifications to estimate the dynamic MVHR in financial, commodity and freight markets (e.g., Kroner and Sultan, 1993; Kavussanos and Nomikos, 2000; Alizadeh et al., 2015; Sun et al., 2018). The MRS-GARCH model adds further flexibility by capturing structural shifts and regime changes in the relationship between spot and futures markets. This is particularly relevant for freight markets, which are characterized by cyclical patterns and sudden shifts in volatility due to their exposure to macroeconomic cycles, geopolitical shocks, and supply-side frictions. Nevertheless, when basis risk is high and correlations are unstable, even dynamic variance-based hedging models fail to effectively capture exposure and yield suboptimal results (Cao and Conlon, 2023; Goswami et al., 2023), which justifies the use of more robust, tail-sensitive methods such as CVaR.

In this study, we compare the performance of the CVaR-based hedging strategy with alternative models proposed in the literature, including rolling window OLS, Bivariate GARCH, and Markov Regime Switching GARCH (MRS-GARCH).

3.1. Conditional Value-at-Risk

While traditional variance-based hedging strategies minimize the variance of the portfolio of spot and futures, they treat gains and losses symmetrically. By contrast, the Conditional Value-at-Risk (CVaR) based hedging strategy, introduced by Rockafellar and Uryasev (2000), focuses explicitly on minimizing the expected tail loss of the portfolio of spot and futures—making it well-suited for hedging shipping freight rates or commodities where downside risk is the primary concern. The CVaR hedging approach seeks to minimize the CVaR of the portfolio consisting of spot and forward positions. CVaR is a coherent and robust risk measure than traditional VaR because minimizing CVaR explicitly focuses on the expected tail loss beyond the VaR threshold.

For a long hedge, the portfolio return at time $t+1$, is given by $R_{h,t+1} = -R_{s,t+1} + h_t R_{f,t+1}$. A loss occurs when $R_{h,t} < 0$ and is expressed by $\mathrm{L}(h,t) = -R_{h,t}$, where $(-R_{h,t})$ can be a random variable with cumulative distribution function $F_{(-R_{h,t})}(z) = P\{-R_{h,t} \le z\}$.

The portfolio VaR at confidence level $\alpha \in (0,1)$ is the threshold loss level such that:

$$VaR_\alpha(-R_{h,t}) = min\left\{z \middle| F_{(-R_{h,t})}(z) \ge \alpha\right\} \tag{3}$$

where $VaR_\alpha(-R_{h,t})$ represents the loss threshold given α percent probability and $F_{(-R_{h,t})}(z)$ is the cumulative distribution of the hedged portfolio. In other words, VaR is the given loss over a certain horizon with confidence level α. For discrete distributions, $VaR_\alpha(-R_{h,t})$ has the feature of non-convex discontinuity with all confidence levels (Rockafellar and Uryasev, 2000).

An alternative risk measure is CVaR, which captures the expected loss beyond the VaR threshold. CVaR goes further by averaging the losses that exceed the VaR threshold, providing a more complete measure of extreme downside risk. For general distributions, the $CVaR_\alpha(-R_{h,t})$ with confidence level of $\alpha \in [0,1]$ is:

$$CVaR_\alpha(-R_{h,t}) = E\{(-R_{h,t}) | (-R_{h,t)} \ge VaR_\alpha(-R_{h,t})\} \tag{4}$$

Following Rockafellar and Royset (2018), a general deviation measure $D(-R_{h,t})$ for a long hedge can be written as:

$$D(-R_{h,t+1}) = D(R_{S,t+1} - h_t R_{F,t+1}) \tag{5}$$

which can be expanded as

$$D(-R_{h,t+1}|\Omega_t) = D(R_{S,t+1}|\Omega_t) + h_t^2 D(R_{F,t+1}|\Omega_t) - 2h_t D(R_{S,t+1}, R_{F,t+1}|\Omega_t) \tag{6}$$

This function generalizes different ways of measuring how far portfolio outcomes deviate from expectations, depending on the chosen risk measure (variance, CVaR, etc.). Minimizing equation (6), yields the optimal hedge ratio (OHR) at time t, defined by

$$h_t^* = D(R_{S,t+1}, R_{F,t+1}|\Omega_t) \,/\, D(R_{F,t+1}|\Omega_t) \tag{7}$$

In essence, this identifies the hedge ratio that minimizes the chosen deviation measure, aligning the hedge with downside risk preferences. When the deviation measure is specified as CVaR, the OHR at time t, that minimizes expected tail loss in equation (6) of minimum CVaR deviation, is determined by

$$h_t^* = Cov(R_{S,t+1}, R_{F,t+1}|\Omega_t) \,/\, CVaR\_Dev_\alpha(R_{F,t+1}|\Omega_t) \tag{8}$$

where

$$CVaR\_Dev_\alpha(X) = CVaR_\alpha\left(\frac{1}{n}\sum_1^n |X - \overline{X}|\right) \tag{9}$$

In equation (9), n represents the sample size, X represents the loss, and the term $\left(\frac{1}{n}\sum_1^n |X - \overline{X}|\right)$ denotes the average absolute deviation of the loss from the mean value over the entire sample period. Accordingly, the OHR differs for long and short positions, directly reflecting asymmetries in return distributions. This is expressed as follows for the long and short hedging cases, respectively[7]:

$$h_t^* = E\left[\left(R_{F,t+1} - R_{S,t+1}\right)\middle|\left(R_{F,t+1}\right) \geq VaR_\alpha\left(R_{F,t+1}\right)\right] / CVaR\_Dev_\alpha\left(R_{F,t+1}\right) \tag{10}$$

$$h_t^* = E\left[\left(R_{F,t+1} - R_{S,t+1}\right)\middle|\left(-R_{F,t+1}\right) \geq VaR_\alpha\left(-R_{F,t+1}\right)\right] / CVaR\_Dev_\alpha\left(-R_{F,t+1}\right) \tag{11}$$

To evaluate risk reduction and hedging effectiveness (HE), we adopt two complementary approaches. First, we apply the traditional variance reduction metric which shows how much of the portfolio's risk is eliminated by hedging; values closer to 1 (or 100 %) indicate stronger risk reduction. HE is measured as the percentage reduction in the variance of the hedged portfolio relative to the unhedged position:

$$HE = [Var(R_s) - Var(R_h)] / Var(R_s) \tag{12}$$

Second, we report the average value of hedged portfolio returns (AVR) for both long and short positions. A negative AVR indicates an average loss over the sample period, while a positive AVR reflects an average gain:

$$AVR_{Short} = \frac{1}{n}\sum_1^n \left[R_{S,t} - h_t^*\left(R_{F,t}\right)\right] \tag{13}$$

$$AVR_{long} = \frac{1}{n}\sum_1^n \left[-R_{S,t} + h_t^*\left(R_{F,t}\right)\right] \tag{14}$$

Furthermore, to capture the downside tail behavior of hedged portfolio returns, we employ two asymmetric risk measures: Value-at-Risk Deviation (VaR_Dev) and Conditional VaR Deviation (CVaR_Dev). These metrics reflect how much losses in the left tail (or the right tail) deviate from average outcomes, allowing for a more nuanced comparison of extreme downside risk across hedging strategies. In intuitive terms, VaR_Dev and CVaR_Dev measured as the difference between the mean and the estimated VaR and CVaR of the hedged portfolio, respectively (see Sarykalin et al., 2008 for more detail). Both are evaluated at a specified confidence level α and are defined as:

$$VaR\_Dev_\alpha\left(R_{h,t}\right) = VaR_\alpha\left(\frac{1}{n}\sum_1^n \left|R_{h,t} - \overline{R}_{h,t}\right|\right) \tag{15}$$

$$CVaR\_Dev_\alpha\left(R_{h,t}\right) = CVaR_\alpha\left(\frac{1}{n}\sum_1^n \left|R_{h,t} - \overline{R}_{h,t}\right|\right) \tag{16}$$

In addition, we utilize two symmetric measures to assess the HE of different strategies: Mean Absolute Deviation (MAD) and Standard Deviation (SD). MAD captures the average absolute distance of returns from their mean treating all deviations equally, while SD reflects overall variability but gives proportionally more influence to larger deviations. Lower values of these measures indicate stronger risk reduction performance:

$$MAD = \frac{1}{n}\sum_1^n \left|R_{h,t} - \overline{R}_{h,t}\right| \tag{17}$$

$$SD = \frac{1}{n}\sum_1^n \sqrt{\left(R_{h,t} - \overline{R}_h\right)^2} \tag{18}$$

3.2. Buffered Probability of Exceedance (bPOE)

The Probability of Exceedance (POE) and the Buffered Probability of Exceedance (bPOE) are probabilistic risk measures associated with VaR and CVaR of the loss distribution of hedged portfolio returns (Mafusalov and Uryasev, 2018). The bPOE offers a complementary perspective by controlling the probability of breaching a given loss threshold. For example, a POE of 10 % at a given threshold implies that in one out of ten scenarios, losses would exceed that level. This probabilistic view provides additional flexibility in

[7] To estimate the hedge ratios based on VaR and CVaR we use Portfolio Safeguard package which efficiently handles risk measures such as VaR and CVaR. (American Optimal Decisions AORDA, 2009; Portfolio Safeguard (PSG), http://www.aorda.com).

managing tail risk (Rockafellar and Uryasev, 2000; Goswami et al., 2023). The POE represents the probability that the portfolio loss exceeds a specified threshold z, and is defined as

$$p_z(-R_{h,t}) = p(-R_{h,t} > z) = 1 - F_{(-R_{h,t})}(z) \tag{19}$$

The POE is equal to 1 minus the cumulative distribution function of the portfolio loss, $F_{(-R_{h,t})}(z)$, which is the negative return on hedged portfolio. As established earlier in equation (6), $F_{(-R_{h,t})}(z)$ is the inverse function of VaR. Hence, the bPOE, $\bar{p}_z(-R_{h,t})$, can be defined as:

$$\bar{p}_z(-R_{h,t}) = \min_{\lambda\geq 0} \mathrm{E}[\lambda(-\mathrm{R}_{\mathrm{h,t}} - \mathrm{z}) + 1]^+ \tag{20}$$

where $[\lambda(-R_{h,t} - z) + 1]^+ = max\{0, \lambda(-R_{h,t} - z) + 1\}$. Intuitively, bPOE estimates the smallest probability with which losses can exceed a threshold z, while also accounting for the size of those exceedances. In practice, this makes bPOE smoother and more reliable for optimization than the plain exceedance probability, which can jump abruptly at specific loss levels. Mafusalov and Uryasev (2018) show that bPOE is equal to $1 - \alpha$ on the interval $E(-R_{h,t}) < z < \sup(-R_{h,t})$, where α is an inverse function of $CVaR_\alpha(-R_{h,t})$, and is the unique solution of equation (19):

$$CVaR_\alpha(-R_{h,t}) = z \tag{21}$$

Therefore, in practical terms, bPOE represents the complement of the probability level at which the CVaR equals a specified threshold z. In other words, while CVaR focuses on the expected loss once the threshold is crossed, bPOE focuses on the likelihood of crossing it in the first place. Optimization of the bPOE depends upon the decision vector h_t, which represents the hedge ratio.

Consider a general portfolio return function for short hedge $R_{h,t+1} = R_{s,t+1} - h_t R_{F,t+1}$, with random coefficients $R_{s,t+1}$ and $R_{F,t+1}$. Then equation (22) implies

$$\bar{p}_z(-R_{h,t}) = \min_{\lambda\geq 0} E\left[\lambda \max_{0\leq t\leq N}(-R_{h,t} - z) + 1\right]^+ = \min_{\lambda\geq 0} E\left[\lambda \max_{0\leq t\leq N}(-R_{S,t+1} + h_t R_{F,t+1} - z) + 1\right]^+ \tag{23}$$

Minimizing the bPOE with regards to $R_{S,t+1}$ and $R_{F,t+1}$, yields

$$\min_{R_{S,t+1} R_{F,t+1}} \bar{p}_z(-R_{h,t}) = \min_{R_{S,t+1} R_{F,t+1}, \lambda\geq 0} E\left[\lambda \max_{0\leq t\leq N}(-R_{S,t+1} + h_t R_{F,t+1} - z) + 1\right]^+ = = \min_{R_{S,t+1} R_{F,t+1}, \lambda\geq 0} E\left[\max_{0\leq t\leq N}(\lambda(-R_{S,t+1} - z) + \lambda h_t R_{F,t+1}) + 1\right]^+ \tag{24}$$

This objective function in equation (24) is piecewise linear and convex in h_t., $R_{S,t+1}$ and $R_{F,t+1}$. Accordingly, for a long hedge, a general portfolio return function is $R_{h,t+1} = -R_{s,t+1} + h_t R_{F,t+1}$, and when minimized, the bPOE can be written as

$$\min_{R_{S,t+1} R_{F,t+1}} \bar{p}_z(-R_{h,t}) = \min_{R_{S,t+1} R_{F,t+1}, \lambda\geq 0} E\left[\lambda \max_{0\leq t\leq N}(R_{S,t+1} - h_t R_{F,t+1} - z) + 1\right]^+ = = \min_{R_{S,t+1} R_{F,t+1}, \lambda\geq 0} E\left[\max_{0\leq t\leq N}(\lambda(R_{S,t+1} - z) - \lambda h_t R_{F,t+1}) + 1\right]^+ \tag{25}$$

Equations (24) and (25) can be formulated as Linear Programing problems. Equations (22)–(25) express how bPOE minimization is implemented for both short and long hedges. Put simply, these formulations determine the hedge ratio that minimizes the probability of extreme losses exceeding a chosen threshold, while accounting for the asymmetry between long and short exposures. This makes the optimization directly applicable to real-world hedging decisions, where the risk profile differs depending on position direction.

Recent work also shows that bPOE minimization can be formulated as a tractable convex program, reinforcing its appeal in risk-averse portfolio settings (Rockafellar and Uryasev, 2020). As stated previously in equations (24) & (25), while bPOE optimization is inherently one-dimensional, real-world hedging decisions often require assessing a range of loss thresholds and risk levels, rather than a single value. To address this, we extend the framework to minimize bPOE across multiple CVaR levels, generating a set of optimal solutions under varying confidence thresholds. In doing so, minimizing both equations (4) and (26) jointly produces overlapping segments of the efficient frontier. This frontier represents a set of Pareto-optimal outcomes in a bi-objective optimization (Mafusalov et al., 2018), where the dual goals are: minimizing CVaR at different confidence levels and minimizing the probability of an adverse event, i.e., the probability that portfolio losses exceed a specific threshold. This framework allows us to visualize and interpret the trade-off between the magnitude and likelihood of extreme losses in a coherent risk management context.

4. Data and preliminary statistics

The data set consists of weekly time series on spot and corresponding Forward Freight Agreements (FFAs) for three main sizes of dry bulk carriers, namely Capesize, Panamax, and Supramax vessels, sourced from the Baltic Exchange. The Baltic Exchange reports daily average spot (trip-charter) freight rates based on defined routes for each vessel size in the dry bulk sector based on the assessments from a panel of shipbrokers. For each vessel size, these freight rates are aggregated to a basket of routes known as average trip-charter (TC) rates including average 5 TC rates for Capesize, average 4 TC rates for Panamax, average 10 TC for Supramax, and average 7 TC for Handysize.,[8,9] The Baltic Exchange also compiles FFA assessments for corresponding average TC rates across vessel size and various tenors, including months, quarters, and calendar years ahead.

For the purpose of this paper, we use spot freight rates representing the average trip-charter rates, along with the corresponding FFAs with a one-quarter maturity for each vessel class. The sample comprises 916 weekly observations covering the period from January 5, 2007 to December 23, 2022. All prices are quoted in USD per day, and reflect Wednesday closing prices, or the next available trading day if Wednesday is a holiday.

Fig. 1 plots the historical series of spot and 1-quarter ahead FFA rates for average 5 TC Capesize, average 4 TC Panamax, and average 10 TC Supramax vessels.[10] All the series exhibit significant fluctuations, with a notable peak just prior to the 2008 global financial crisis. For instance, the 1-quarter ahead FFA for the Panamax average of four trip-charter rates surged to 80,600 USD/day in June 2008, before collapsing to $4400 USD/day by the end of that year - equivalent to a 95 % reduction in value. After the financial crisis, freight volatility remained elevated, driven by the uneven global recovery, fluctuations in commodity trade, and persistent oversupply in the dry bulk fleet. While spot and FFA rates tend to move together, their correlation is relatively low and spot rates are more volatile. This is expected, as quarterly FFA contracts reflect the market's expectation of average freight rates over the coming quarter, resulting in lower short-term variability compared with spot rates.

Descriptive statistics of the weekly return series for spot and corresponding quarterly FFA rates for different sizes of dry bulk carriers are presented in Table 1. A comparison of standard deviations reveals that spot returns are consistently more volatile than FFA returns across all vessel sizes. Moreover, the volatility of both spot and FFA returns increases with vessel size, with larger vessels such as Capesize exhibiting higher return variability than smaller ones like Supramax. This is a well-documented pattern in the literature (e.g., Kavussanos, 1996).

Turning to the estimated skewness coefficients for spot and FFA return series, we observe that 5 out of 6 return distributions are negatively skewed, suggesting that dry bulk freight rates are more prone to large negative returns than positive ones. Moreover, all kurtosis coefficients exceed three, highlighting the fact that both spot and FFA return distributions are leptokurtic, with sharp peaks and heavy tails relative to the normal distribution. These departures from normality are statistically supported by the Jarque and Bera (1980) test results at conventional significance levels. Such non-normal distributional features – particularly asymmetry and fat tails - have important implications for the hedge ratio estimation, potentially leading to inefficient hedging strategies. Moreover, recent work in commodity markets has demonstrated the importance of using tail-sensitive risk metrics, such as CVaR, especially in the presence of non-normal features like asymmetry and excess kurtosis (Byers et al., 2021).

Further, the results of Ljung and Box (1978) tests applied to both return levels and squared returns are reported in Table 2. The LB-Q (14) test statistics indicate a high degree of autocorrelation in the spot and FFA return series across all vessel sizes. Similarly, the LB-Q^2(14) test results reveal significant autocorrelation in the squared returns, suggesting the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effects. These findings are further corroborated by Engle's (1982) ARCH(4) test, which confirms statistically significant ARCH effects in both spot and FFA return series for all vessel sizes. The presence of such effects justifies the use of time-varying models like GARCH in hedge ratio estimation.

Table 2 also reports the results of unit root tests conducted on the log-levels and log-returns of spot and FFA rates for different sizes of dry bulk carriers. The tests include the augmented Dickey and Fuller (ADF, 1979), Phillips and Perron (PP, 1988) and Kwiatkowski et al. (KPSS, 1992) tests. For all the log-level series, the KPSS test fails to reject the null hypothesis of stationarity, while the ADF and PP tests reject the null of a unit root only at the 10 % significance level. In contrast, all three tests strongly support stationarity in the log-return series.

Taken together, Tables 1 and 2 highlight key features of dry bulk freight returns. Spot rates are more volatile than FFAs, with variability increasing by vessel size, particularly for Capesize. Negative skewness and excess kurtosis confirm the heavy-tailed and asymmetric nature of freight returns, while the unit root tests verify that log-returns are stationary and suitable for econometric modeling. These characteristics reinforce the need for tail-sensitive hedging frameworks such as CVaR and bPOE.

Asymmetry and leptokurtosis in the return distribution of hedged portfolios can significantly distort the estimation of both variance and CVaR, rendering traditional minimum variance approaches potentially ineffective (e.g., Sukcharoen and Leatham, 2017). Fig. 2 illustrates the empirical (sample) distributions of spot and corresponding FFA series, overlaid with the normal distribution for comparison. All distributions display signs of negative skewness and excess kurtosis. A comparison of the tails reveals that dry bulk freight rates are more susceptible to extreme negative movements than to upward spikes. These distributional characteristics underscore the need for hedging models that can capture tail asymmetry and the non-uniform decay of distribution tails. Properly recognizing and modeling these features is crucial for accurate risk measurement, effective hedging strategies and robust empirical analysis in freight rates.

Furthermore, the sample period seems to include significant events such as the 2008 global financial crisis and COVID-19, which

[8] The definition of the Baltic shipping routes and composition of the basket of freight rates in each sector can be found on the Baltic Exchange website (https://www.balticexchange.com/en/index.html).

[9] Baltic Exchange also aggregates these freight rates in the form of indices known as the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI), and the Baltic Supramax Index (BSI).

[10] We do not include Handysize market in our analysis because the there was no trading activities in the FFA market for Handysize vessels in out sample period.

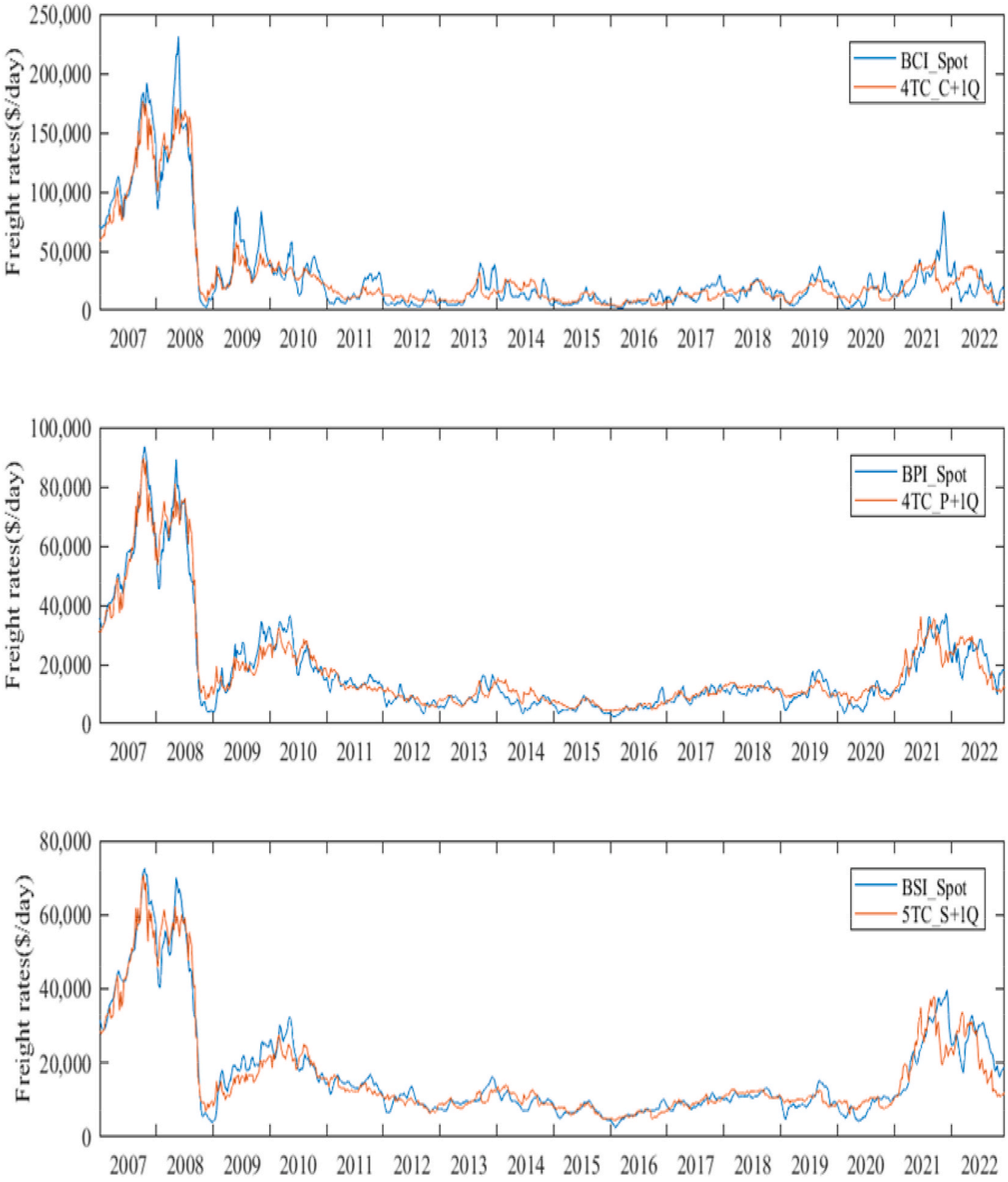

Fig. 1. Historical Spot and quarterly FFAs prices for different size dry bulk carriers
Notes: The figure plots weekly spot and 1-quarter ahead Forward Freight Agreement (FFA) rates for Capesize, Panamax, and Supramax vessels. Data are sourced from the Baltic Exchange and span the period from January 5, 2007 to December 23, 2022. All rates are quoted in USD per day and correspond to Wednesday closing prices (or the next trading day in case of a holiday).

resulted in structural changes and regime shifts in volatility and correlation dynamics. Such structural changes can adversely affect the performance of models that rely on stable parameter estimates (see Goswami et al., 2023), whereas more adaptive approaches such as dynamic CVaR optimization appear more robust (e.g., Melnikov and Smirnov, 2012). Although some alternative hedging strategies such as the MRS-GARCH model explicitly account for regime shifts, the CVaR-based approach can be more appropriate because it minimizes the tail-risk while it is flexible and dynamically adjusts to changes in the market as the estimation window is updated in the sample used for CVaR optimization.

Table 1
Descriptive statistics of dry bulk spot and FFA weekly returns.

	Capesize		Panamax		Supramax	
	BCI 4 TC	4 TC_C+1Q	BPI 4 TC	4 TC_P+1Q	BSI 5 TC	5 TC_S+1Q
Observations	800	800	800	800	800	800
Mean	−0.0008	−0.0009	−0.0004	−0.0005	−0.0003	−0.0005
Median	−0.0023	0.0010	−0.0001	0.0004	0.0013	0.0022
Std. Dev.	0.08	0.06	0.05	0.04	0.03	0.03
Skewness	0.13	−0.84	−0.22	−0.57	−0.18	−1.15
Kurtosis	1.58	8.97	2.69	5.08	6.3	5.78
Jarque-Bera	86.295	2793	250.1	908.4	1335.3	1298.6
LB-Q(14)	264.8 [0.000]	25.378 [0.031]	148.89 [0.000]	29.933 [0.008]	476.04 [0.000]	24.992 [0.035]
LB-Q^2(14)	121.22 [0.000]	13.573 [0.482]	156.62 [0.000]	177.93 [0.000]	466.72 [0.000]	110.85 [0.000]
ARCH-LM (4)	79.625 [0.000]	4.2588 [0.372]	81.8 [0.000]	82.777 [0.000]	264.17 [0.000]	55.47 [0.000]

Sample period spans from January 5, 2007 to December 23, 2022 covering Capesize, Panamax, and Supramax. The Jarque-Bera is the test employed to assess the null hypothesis of normality in return distributions. LB-Q(14) and LB-Q^2(14) are the Ljung and Box (1978) tests for autocorrelation in returns and squared returns, respectively. The ARCH-LM (4) test is the Engle (1982) test, used to detect the presence of Autoregressive Conditional Heteroscedasticity.

Table 2
Unit root tests for dry bulk spot and FFAs.

	Log Levels					
	BCI 4 TC	4 TC_C+1Q	BPI 4 TC	4 TC_P+1Q	BSI 5 TC	5 TC_S+1Q
ADF	−3.852***	−3.185***	−2.751***	−2.381***	−3.067***	−2.476***
PP	−4.064***	−3.015***	−2.733***	−2.169***	−2.505***	−2.192***
KPSS	2.866	3.744	2.955	3.346	2.943	3.161
	Log returns					
ADF	−9.665***	−8.845***	−9.265***	−8.664***	−8.341***	−8.291***
PP	−16.64***	−29.84***	−17.31***	−30.8***	−12.15***	−28.81***
KPSS	0.04041	0.03537	0.04972	0.05312	0.05684	0.07514

Unit root tests for log levels and log returns are conducted using the Augmented Dickey and Fuller (ADF, 1979) unit root test, the Phillips and Perron (PP, 1988) unit root test, and the Kwiatkowski et al. (KPSS, 1992) stationarity test. *** indicates rejection of the null hypothesis of unit root at the 1 % significance level. The 1 % and 5 % significance levels for ADF and PP tests are −3.438, and −2.864, respectively. See also notes in Table 1.

5. Empirical results

5.1. Static hedging results

To investigate the performance of minimum CVaR hedging relative to alternative strategies, including minimum variance and naïve (one-to-one) hedging, we first report the results of static hedging strategies over both in-sample and out-of-sample periods across the three dry bulk sub-markets. These results are presented in Tables 3 and 4, respectively. The comparison is based on several performance metrics: variance reduction (VR), hedging effectiveness (HE), average value of portfolio returns (AVPR), mean absolute deviation (MAD), 90 % VaR Deviation (VaR_Dev), and 90 % CVaR Deviation (CVaR_Dev). For the minimum CVaR deviation strategy, the results are reported separately for both long and short hedging positions, to account for asymmetries in the distribution of hedged portfolio returns.

In general, the minimum CVaR deviation strategy outperforms both the minimum variance and naïve hedging strategies across multiple hedging effectiveness measures. Based on the traditional variance reduction metric, CVaR-based hedging performs comparably to alternative approaches in the in-sample period (Table 3). However, over the out-of-sample period (Table 4), the CVaR strategy consistently outperforms all other methods across the three dry bulk sub-markets. For example, in the out-of-sample period, with extreme market stress such as the post–2011 shipping downturn and COVID-19 disruptions, the minimum CVaR approach achieves up to 18.26 % variance reduction in Capesize compared to 16.29 % for OLS, while also lowering 90 % CVaR deviation from 0.3585 (OLS) to 0.3525.

The improvement in performance is particularly evident when the distribution of the underlying hedged portfolios significantly deviates from normality due to fat tails and asymmetry. In such cases, the minimum CVaR approach captures tail risk more effectively than symmetric hedging strategies based on variance minimization. Conversely, when return distributions are approximately normal, the performance of the CVaR and minimum variance strategies tends to converge. The naïve hedging strategy demonstrates the weakest performance, especially in terms of variance reduction, largely due to its failure to account for differences in spot and FFA volatility and the low correlation between them (Kavussanos and Visvikis, 2010). Comparable issues have been documented in the context of jet fuel hedging (Cao and Conlon, 2023), where imperfect correlations between the hedged asset and its proxy lead to significant basis risk and diminished hedging performance (see also Goswami et al., 2023).

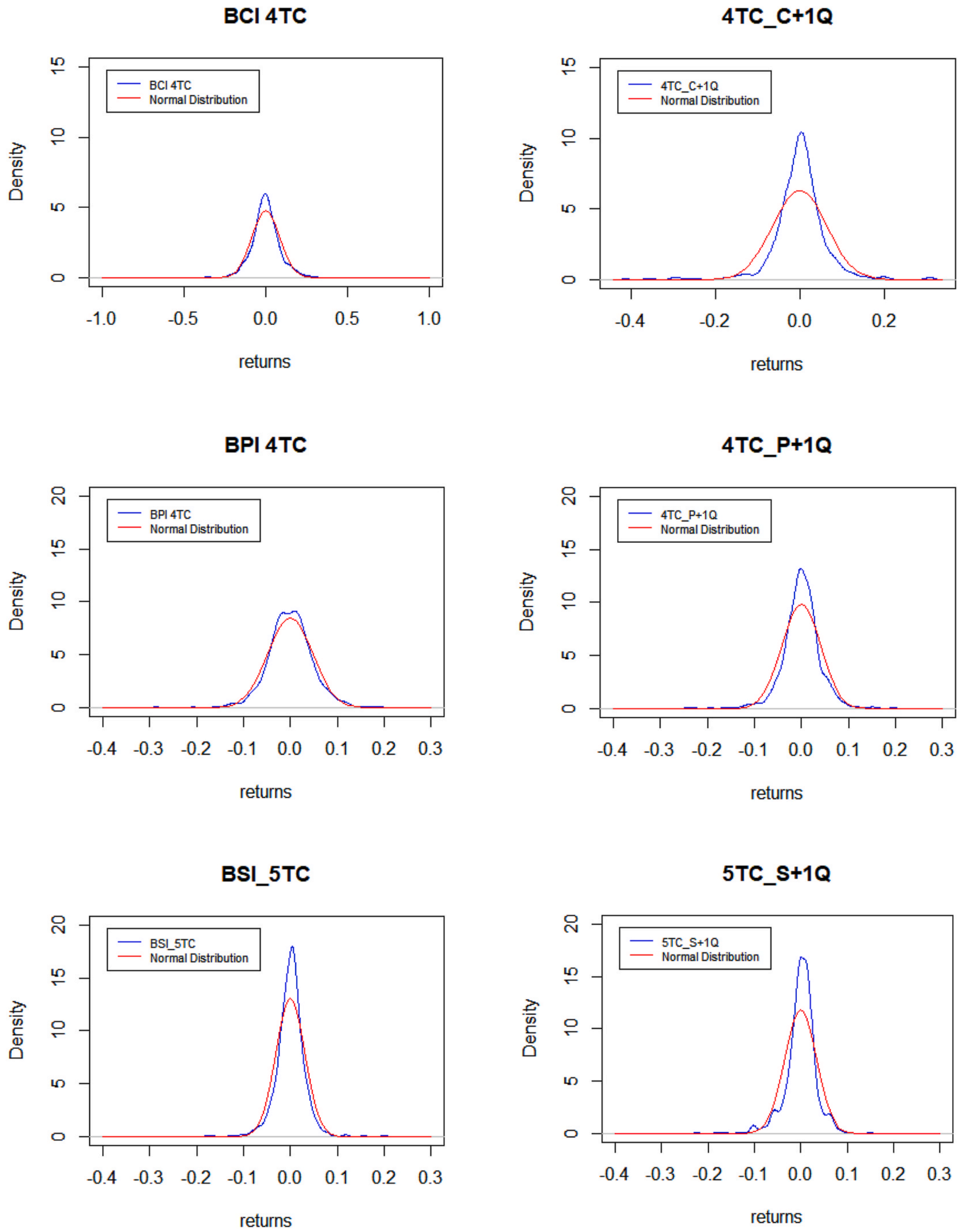

Fig. 2. Empirical distributions of spot and FFA returns vs. Normal Distribution
Notes: The figure compares the empirical distribution of weekly log returns for spot and 1-quarter ahead FFA rates across Capesize, Panamax, and Supramax vessels with the standard normal distribution. The plotted distributions are based on data from the Baltic Exchange for the period January 5, 2007 to December 23, 2022. Heavy tails and asymmetry are evident, particularly in spot return series, highlighting the need for tail-sensitive hedging strategies.

In addition to variance-based metrics, we also assess performance using average portfolio return (AVR) and downside risk measures. For instance, a larger and positive average value of hedged portfolio returns (AVR) indicates better performance over the sample period for each vessel type. The results show that the minimum CVaR deviation approach generates a relatively higher AVR compared to both the minimum variance and naïve hedging strategies in more than half of the in-sample and out-of-sample cases. This suggests that the CVaR-based method is more effective in mitigating negative skewness and fat tails in return distributions. Additional downside

Table 3
In-sample performance of static hedging strategies.

Capesize	Variance	Variance Reduction	HE	AVR	MAD	90 % VaR_Dev	90 % CVaR_Dev
Unhedged	0.0302						
Naïve	0.0213	0.0089	29.47 %	**0.0014**	0.1014	0.1492	0.2739
OLS	0.0207	0.0095	31.46 %	0.0006	0.0973	0.1349	0.2662
CVaR(short)	**0.0205**	**0.0097**	**32.12 %**	0.0004	**0.0970**	**0.1317**	**0.2657**
CVaR(long)	**0.0206**	**0.0096**	**31.79 %**	0.0005	**0.0967**	**0.1342**	**0.2466**
Panamax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0136						
Naïve	0.0135	0.0001	0.74 %	0.0003	0.0845	0.1249	0.2019
OLS	**0.0108**	**0.0028**	**20.59 %**	−0.0011	**0.0729**	**0.1130**	**0.1732**
CVaR(short)	**0.0107**	**0.0029**	**21.32 %**	**0.0014**	**0.0729**	**0.1103**	**0.1737**
CVaR(long)	**0.0108**	**0.0028**	**20.59 %**	**0.0012**	**0.0729**	0.1148	0.1932
Supramax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0063						
Naïve	0.0084	−0.0021	−33.33 %	−0.0004	0.0643	0.0998	0.1538
OLS	0.0054	0.0009	14.29 %	−0.0010	0.0495	0.0768	**0.1213**
CVaR(short)	**0.0053**	**0.0010**	**15.87 %**	**−0.0001**	**0.0487**	**0.0742**	**0.1219**
CVaR(long)	**0.0053**	**0.0010**	**15.87 %**	**−0.0001**	**0.0488**	**0.0739**	0.1410

The in-sample period for Capesize, Panamax, and Supramax spans from January 5, 2007 to December 28, 2011. The weekly sample is constructed using Wednesday price observations. HE represents the hedge effectiveness; AVR is the average hedged portfolio return, MAD is mean absolute deviation; 90 % VaR_Dev is the value of VaR Deviation at the 90 % confidence level, and 90 % CVaR_Dev is the value of CVaR Deviation at the 90 % confidence level. Bold values indicate the best-performing hedging strategy for each vessel type under the respective metric. For the CVaR-based strategy, the long and short results are evaluated independently and highlighted in bold if they outperform all other strategies in their respective direction. If a symmetric strategy (e.g., OLS) provides the best overall performance, but the CVaR-hedge outperforms it in one direction only (long or short), both values are bolded to reflect the CVaR strategy's outperformance in one direction.

Table 4
Out-of-sample performance of static hedging strategies.

Capesize	Variance	Variance Reduction	HE	AVR	MAD	90 % VaR_Dev	90 % CVaR_Dev
Unhedged	0.0448						
Naïve	0.0393	0.0055	12.25 %	−0.0047	0.1439	**0.2285**	0.3670
OLS	0.0375	0.0073	16.29 %	−0.0050	**0.1426**	0.2475	0.3585
CVaR(short)	**0.0366**	**0.0082**	**18.26 %**	**−0.0040**	0.1430	0.2403	**0.3525**
CVaR(long)	**0.0371**	**0.0077**	**17.19 %**	**−0.0041**	**0.1427**	**0.2341**	**0.3530**
Panamax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0119						
Naïve	0.0129	−0.0010	−8.40 %	−0.0007	0.0892	0.1277	0.2017
OLS	0.0113	0.0006	6.67 %	**−0.0006**	0.0820	0.1250	0.1851
CVaR(short)	**0.0111**	**0.0008**	**7.50 %**	**−0.0006**	**0.0816**	**0.1249**	**0.1850**
CVaR(long)	**0.0111**	**0.0009**	**6.72 %**	**−0.0006**	**0.0819**	**0.1216**	**0.1806**
Supramax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0041						
Naïve	0.0050	−0.0009	−21.95 %	−0.0002	0.0539	0.0781	0.1369
OLS	0.0039	0.0002	4.88 %	−0.0008	0.0430	**0.0557**	**0.1050**
CVaR(short)	**0.0035**	**0.0006**	**14.63 %**	**0.0007**	**0.0426**	**0.0546**	**0.1047**
CVaR(long)	**0.0035**	**0.0006**	**14.63 %**	**0.0007**	**0.0426**	0.0569	0.1110

The out-of-sample period for Capesize, Panamax, and Supramax spans from January 4, 2011 to December 28, 2022. The weekly sample is constructed using Wednesday price observations. See also notes in Table 3.

risk measures, including 90 % CVaR deviation and 90 % VaR deviation, further confirm the superior performance of the minimum CVaR deviation strategy in both in-sample and out-of-sample periods and across all vessel sectors. By contrast, the naïve hedging strategy consistently yields the highest values of CVaR deviation, indicating the poorest performance in terms of downside risk mitigation. In nearly all cases, the CVaR method delivers lower downside risk than both the naïve hedge and the minimum variance hedge (via OLS).

As noted by Wang et al. (2015), the out-of-sample performance of hedging models typically falls short of their in-sample performance due to estimation errors in model parameters. In general, out-of-sample performance is lower than in-sample results, due to forecasting errors in the estimation of hedge ratios (Alizadeh et al., 2015). Our empirical findings are consistent with this view; out-of-sample results are not superior to in-sample results across any of the hedging strategies or dry bulk sub-markets considered.

Overall, based on the traditional measure of hedging effectiveness, minimum CVaR deviation approach either outperforms or performs comparably to benchmarks, in line with Shrestha et al. (2018). When evaluated with downside-focused metrics, such as AVR, 90 % VaR deviation, and 90 % CVaR_deviation, the minimum CVaR deviation strategy demonstrates superior performance relative to both the minimum variance and naïve hedging approaches. This finding echoes Melnikov and Smirnov (2012), who demonstrate that CVaR-based hedging strategies offer more reliable protection against extreme downside risk.

5.2. Dynamic hedging results

Next, we compare the performance of the minimum CVaR deviation strategy against alternative hedging approaches based on dynamic models, which re-estimate the hedge ratios each week using a rolling window for both in-sample and out-of-sample periods. The alternative dynamic hedging strategies include the rolling window OLS, the Markov Regime Switching GARCH (MRS-GARCH) model (Alizadeh et al., 2015), and the Bivariate GARCH model (Souhir et al., 2019). We begin with the rolling window OLS where hedge ratios are re-estimated by applying an OLS regression over a fixed-size window. At each step, the sample window is updated by adding a new observation at the end and dropping the earliest one, ensuring the window length remains constant. The MRS-GARCH model is a dynamic framework that allows for regime shifts, according to the evolving state of the market, by estimating the time-varying regime probabilities assuming two latent regimes (see Alizadeh et al., 2015). Lastly, the Bivariate GARCH model uses the forecast of covariance between spot and FFA returns and variance of FFA returns to obtain the dynamic hedge ratio each period.

The in-sample and out-of-sample results for the five dynamic hedging models across different dry bulk sub-markets are presented in Tables 5 and 6, respectively. In the in-sample period results reveal that the minimum CVaR hedging method consistently outperforms the alternative strategies for all vessel sizes. For instance, in the case of Capesize vessels the HE of the minimum CVaR approach for long and short hedges are 55.30 % and 55.63 %, respectively, compared to 21.52 %, 30.08 % and 38.08 %, for rolling OLS, BGARCH and MRS-GARCH, respectively. For the Panamax sector, the HE of CVaR-based values for long and short hedges are 36.03 % (long hedge) and 34.55 % (short hedge), again outperforming both BGARCH and MRS-GARCH. Interestingly, the rolling OLS model achieves a HE of 47.79 %, which exceeds alternative methods; suggesting that in some market segments, simpler models may still offer competitive results. The results for the Supramax sector are similar to those of the Capesize, with the minimum CVaR method delivering higher HE than all other alternatives. While average hedged portfolio returns (AVR) and mean absolute deviation (MAD) do not show substantial differences across strategies and vessel sizes, the 90 % VaR_deviation (VaR_Dev 90 %) and 90 % CVaR_deviation (CVaR_Dev 90 %) are consistently lower for the minimum CVaR hedging strategy, indicating better downside risk control compared to

Table 5
In-sample performance of different dynamic hedging strategies.

Capesize	Variance	Variance Reduction	HE	AVR	MAD	90 % VaR_Dev	90 % CVaR_Dev
Unhedged	0.0302						
Rolling OLS	0.0237	0.0065	21.52 %	0.0005	0.1024	0.1406	0.2869
BGARCH	0.0210	0.0092	30.46 %	**0.0006**	0.0978	0.1406	0.2633
MRS	0.0187	0.0115	38.08 %	−0.0006	**0.0926**	0.1263	0.2512
CVaR(short)	**0.0135**	**0.0167**	**55.30 %**	0.0005	**0.0877**	**0.1220**	**0.2293**
CVaR(long)	**0.0134**	**0.0168**	**55.63 %**	**0.0006**	0.1330	**0.1206**	**0.2227**
Panamax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 %VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0136						
Rolling OLS	**0.0072**	**0.0065**	**47.79 %**	−0.0206	**0.0681**	**0.1014**	**0.1492**
BGARCH	0.0110	0.0026	19.12 %	−0.0008	0.0731	0.1038	0.1738
MRS	0.0100	0.0036	26.47 %	−0.0010	0.0710	0.1071	0.1663
CVaR(short)	0.0087	0.0049	36.03 %	**−0.0007**	0.0691	0.1021	0.1611
CVaR(long)	0.0089	0.0047	34.55 %	**0.0027**	**0.0668**	**0.1013**	**0.1608**
Supramax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0063						
Rolling OLS	0.0061	0.0002	3.17 %	−0.0029	**0.0439**	**0.0622**	**0.0966**
BGARCH	0.0054	0.0009	14.29 %	−0.0012	0.0486	0.0729	0.1213
MRS	0.0072	−0.0009	−14.29 %	−0.0004	0.0597	0.0892	0.1472
CVaR(short)	**0.0039**	**0.0024**	**38.10 %**	**0.0043**	0.0565	0.0792	0.1006
CVaR(long)	**0.0036**	**0.0027**	**42.86 %**	**−0.0003**	0.0546	0.0767	0.0979

The in-sample period for Capesize, Panamax, and Supramax spans from January 5, 2007 to December 28, 2011. The weekly sample is constructed using Wednesday price observations. MRS refers to the Markov Regime Switching model. BGARCH denotes the Bivariate Constant Conditional Correlation GARCH model. HE represents the hedge effectiveness; AVR is the average value of hedged portfolio, MAD is mean absolute deviation; 90 % VaR_Dev is the value of VaR Deviation at the 90 % confidence level, and 90 % CVaR_Dev is the value of CVaR Deviation at the 90 % confidence level. Bold values indicate the best-performing hedging strategy for each vessel type under the respective metric. For the CVaR-based strategy, the long and short results are evaluated independently and highlighted in bold if they outperform all other strategies in their respective direction. If a symmetric strategy (e.g., OLS) provides the best overall performance, but the CVaR-hedge outperforms it in one direction only (long or short), both values are bolded to reflect the CVaR strategy's outperformance in one direction.

Table 6
Out-of-sample performance of different dynamic hedging strategies.

Capesize	Variance	Variance Reduction	HE	AVR	MAD	90 % VaR_Dev	90 % CVaR_Dev
Unhedged	0.0448						
Rolling OLS	0.0354	0.0094	20.98 %	−0.0049	0.1419	0.2541	0.3517
BGARCH	0.0349	0.0099	22.10 %	−0.0052	0.1406	0.2459	0.3480
MRS	0.0262	0.0186	41.52 %	−0.0137	**0.1163**	**0.1922**	0.3058
CVaR(short)	**0.0258**	**0.0190**	**42.41 %**	**−0.0030**	**0.1129**	0.2238	**0.3044**
CVaR(long)	**0.0248**	**0.0200**	**44.64 %**	**0.0099**	0.1196	**0.1879**	**0.2913**
Panamax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0119						
Rolling OLS	**0.0070**	**0.0049**	**40.83 %**	−0.0029	0.0838	**0.1121**	**0.1567**
BGARCH	0.0103	0.0016	13.45 %	**0.0002**	0.0811	0.1250	0.1792
MRS	0.0090	0.0029	24.37 %	−0.0009	0.0784	0.1224	0.1650
CVaR(short)	0.0084	0.0035	29.42 %	−0.0012	**0.0778**	0.1122	0.1646
CVaR(long)	0.0085	0.0034	28.57 %	−0.0010	**0.0776**	**0.1119**	0.1638
Supramax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0041						
Rolling OLS	0.0097	−0.0056	−5.56 %	−0.0004	0.0790	0.1147	0.1654
BGARCH	0.0040	0.0001	2.44 %	**−0.0003**	0.0685	0.0773	0.1103
MRS	0.0037	0.0004	11.11 %	−0.0009	**0.0410**	0.0611	**0.0988**
CVaR(short)	**0.0036**	**0.0005**	**12.20 %**	−0.0021	0.0469	**0.0589**	0.1062
CVaR(long)	**0.0036**	**0.0005**	**12.20 %**	**0.0001**	0.0464	**0.0574**	**0.0963**

The out-of-sample period for Capesize, Panamax, and Supramax spans from January 4, 2011 to December 28, 2022. The weekly sample is constructed using Wednesday price observations. See also notes in Table 5.

the alternatives across all vessel sizes.

Turning to out-of-sample results in Table 6, the minimum CVaR hedging method again outperforms the alternative strategies across all vessel sizes, based on the HE measures. For the Capesize market the estimated HE of the CVaR method is 42.53 % for short and 44.98 % for long hedges compared to 21.16 %, 22.05 % and 41.87 % for Rolling OLS, BGARCH, and MRS-GARCH, respectively. In the Panamax sector, the CVaR-based HE values are 29.16 % for short and 27.50 % for long hedges while the HE values for rolling OLS, BGARCH, and MRS-GARCH are 40.83 %, 17.5 %, and 25.00 %, respectively. In this case, rolling OLS achieves the highest HE. As for the Supramax sector, the out-of-sample results are more mixed. The HE for the CVaR method is 5.56 % for both long and short hedges, while rolling OLS, BGARCH and MRS-GARCH produce HE values of 5.56 %, 2.78 %, and 11.11 %, respectively. While the average hedged portfolio returns (AVR) are somewhat mixed across strategies MAD, 90 % VaR_deviation and 90 % CVaR_deviation tend to be generally better for the minimum CVaR hedging method, confirming its relative advantage in controlling downside risk in the out-of-sample period. Specifically, the results in Table 6 show that CVaR-based strategies deliver the largest relative gains in vessel segments with higher volatility, heavier tails, and greater basis risk. In the dynamic setting, the Capesize CVaR hedge reduces 90 % CVaR deviation to 0.2913 versus 0.3058 for the best-performing benchmark (MRS-GARCH). This stronger performance of Capesize aligns with its market profile as the most volatile segment in our sample (Table 1) and the one with the highest basis risk, where unstable spot–FFA correlations weaken the effectiveness of variance-based hedging strategies.

It is also worth noting that CVaR's incremental value is stronger for tail-risk measures than for variance alone. In the static out-of-sample Capesize results (Table 4), the 90 % CVaR deviation falls from 0.3585 under OLS to 0.3525 with CVaR, the clearest tail-risk gain. In Supramax dynamics (Table 6), the deviation declines from 0.0988 under MRS-GARCH to 0.0963 with CVaR, showing benefits beyond the most volatile market. Moreover, CVaR achieves far higher hedging effectiveness: for Capesize in-sample (Table 5), HE reaches 55 % versus 21.5 % for rolling OLS, underscoring the robustness of downside-focused strategies.

Furthermore, Figs. 3–5 display the estimated time-varying hedge ratios generated by the five hedging strategies across the Capesize, Panamax and Supramax markets. The rolling window OLS hedge ratios exhibit a relatively stable pattern across all vessel types; however, this method shows the weakest performance in terms of the average value of portfolio returns (AVR). In contrast, the MRS-GARCH model produces highly volatile hedge ratios, which may be impractical due to the need for frequent position adjustments and the associated transaction costs from buying or selling FFAs. The Bivariate GARCH model provides more stable hedge ratios than the MRS-GARCH, yet still entails considerable adjustment frequency, limiting its practical appeal under high transaction costs (e.g., see Souhir et al., 2019). In comparison, the minimum CVaR deviation strategy yields smoother and more stable hedge ratios which points to the distinct advantage of CVaR-based models. Notably, the minimum CVaR long and short strategies led to differentiated hedge ratios, demonstrating the model's ability to capture asymmetries in the return distribution. In addition, the lower volatility in the hedge ratios derived from the minimum CVaR approach implies reduced adjustment frequency and therefore lower transaction costs,

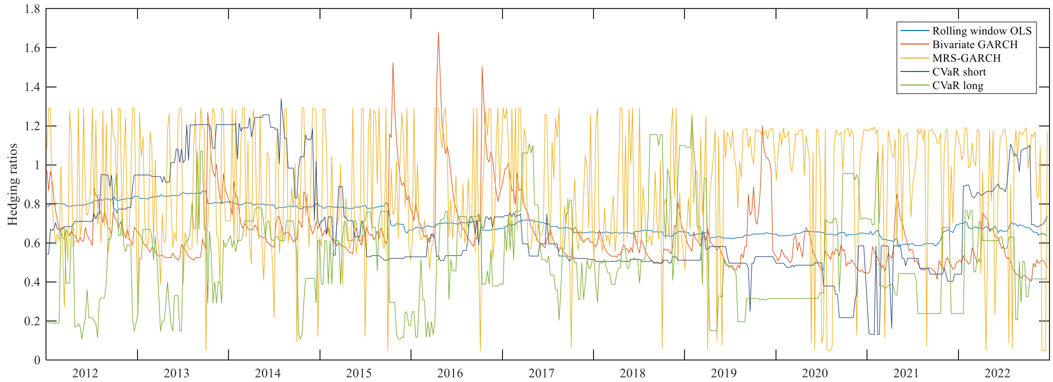

Fig. 3. Estimates of out-of-sample dynamic hedging ratios for Capesize
Notes: This figure displays the weekly dynamic out-of-sample hedge ratios for Capesize vessels estimated using five different methods: Naïve, Rolling OLS, Bivariate GARCH, MRS-GARCH, and Minimum CVaR Deviation - for both long and short hedge positions.

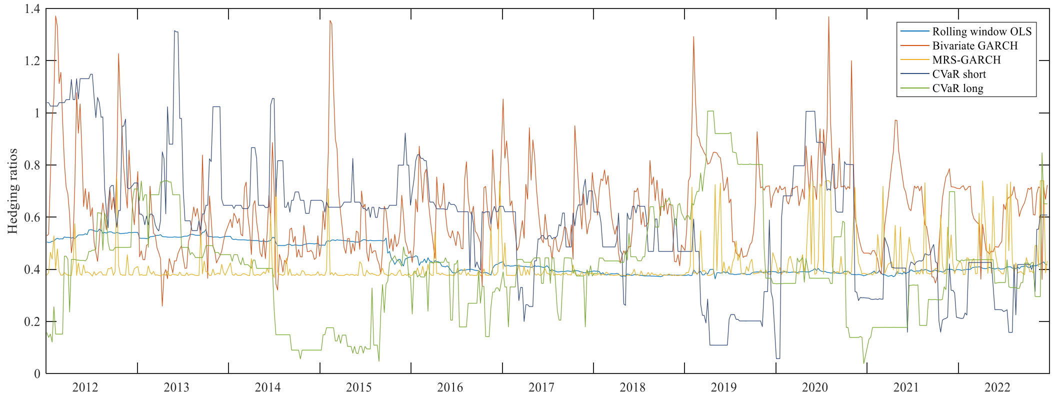

Fig. 4. Estimates of out-of-sample dynamic hedging ratios for Panamax
Notes: This figure displays the weekly dynamic out-of-sample hedge ratios for Panamax vessels estimated using five different methods: Naïve, Rolling OLS, Bivariate GARCH, MRS-GARCH, and Minimum CVaR Deviation - for both long and short hedge positions.

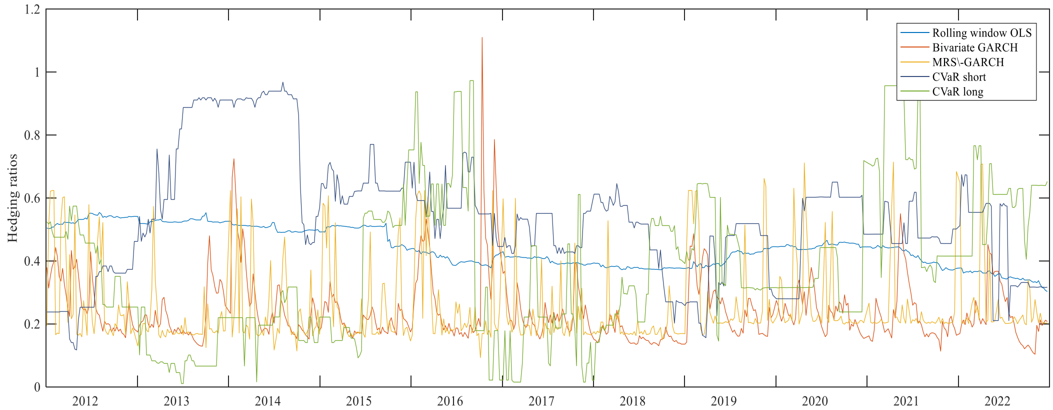

Fig. 5. Estimates of out-of-sample dynamic hedging ratios for Supramax
Notes: This figure displays the weekly dynamic out-of-sample hedge ratios for Supramax vessels estimated using five different methods: Naïve, Rolling OLS, Bivariate GARCH, MRS-GARCH, and Minimum CVaR Deviation - for both long and short hedge positions.

which is particularly important in the context of dynamic hedging strategies.

In addition, as suggested by Melnikov & Smirnov (2012), these hedge ratios react primarily to persistent changes in downside risk rather than to transient fluctuations, thereby minimizing unnecessary rebalancing.[11] From a practical standpoint, this stability is highly valuable for shipowners, charterers, and trading firms, since fewer hedge adjustments translate into lower transaction costs, reduced operational complexity, and less exposure to liquidity constraints in the FFA market. In volatile freight environments, where bid–ask spreads can widen quickly, smoother hedge ratios also improve execution certainty and help align hedging strategies with internal risk limits and capital allocation policies. Thus, beyond statistical performance, the CVaR-based approach offers tangible cost savings and more reliable implementation for market participants.

A common feature of downside risk optimization using CVaR approach in markets characterized by low spot-futures correlations, high basis risk, and non-normal, heavy-tailed distributions, is that hedge ratios can exceed 100 % level – as seen in Fig. 6. Prior studies have also shown that when the hedging instrument is imperfectly correlated with the underlying exposure, optimal hedge ratios derived from CVaR or related risk measures can exceed nominal exposure (e.g., Cao et al., 2010; Melnikov and Smirnov, 2012; Goswami et al., 2023). In addition, in markets where prices follow mean reverting processes, the volatility of forward or futures prices tend to be lower than volatility of spot prices. Thus, to hedge a unit change in spot price more than one unit of forward or futures should be used (Alizadeh et al., 2015; Sun et al., 2018; Shrestha et al., 2018).

Finally, to assess the robustness of the minimum CVaR strategy with respect to the window size used in hedge ratio estimation we follow Pavlikov and Uryasev (2014) using different CVaR estimation windows. Specifically, we evaluate the out-of-sample performance of the CVaR-based hedging strategy using a range of rolling window sizes (125, 150, 175, and 200 weeks). Fig. 6 illustrates the impact of rolling window length on CVaR hedge ratio estimates for Capesize vessels. The hedge ratios generated using a shorter window of 125 weeks respond more rapidly to recent market conditions and exhibit higher volatility. In contrast, the longer rolling window of 200 weeks produces smoother hedge ratios with slower responsiveness to market changes. The intermediate 150-week rolling window used in the study seems to provide a balance between these extremes. These results underscore the importance of window selection in risk-sensitive hedging frameworks, where the trade-off between adaptability and stability affects both risk coverage and implementation costs.

A more formal assessment of the impact of window length on the out-of-sample hedging performance of the CVaR strategy in Table 7. Results reveal that changes in window size have minimal impact on the relative performance of the minimum CVaR strategy relative to the alternatives. These findings highlight the robustness and stability of the CVaR-based approach and further support its value as a coherent and efficient risk optimization technique for hedge ratio estimation in dry bulk freight markets.

5.3. *Distributions of portfolio returns*

As further assessment, we conduct additional statistical analysis on the distribution of out-of-sample hedged portfolio returns derived from the minimum CVaR deviation strategy. The distributions for out-of-sample short and long hedged portfolio returns across the three size vessel classes are presented in Fig. 7, along with the standard deviation (Std_Dev), 90 % CVaR_deviation, 90 % VaR_-deviation, and Maximum Loss Deviation (MLD). MLD is defined as the difference between the maximum loss and the mean of the hedged portfolio return distribution. The visual annotations show that CVaR deviation extends further into the left tail than VaR deviation, capturing not only the cutoff point for extreme losses but also their average magnitude. The inclusion of MLD highlights the most adverse observed outcome relative to the mean. Taken together, these cues demonstrate the added value of CVaR in quantifying downside risk beyond variance-based measures.

Compared to the spot and FFA distributions (Fig. 2), the hedged returns appear more symmetric and closer to normal, underscoring the effectiveness of CVaR-based strategy in mitigating skewness and excess kurtosis. This mitigative effect is particularly important given the documented skewness and kurtosis in dry bulk freight returns (Nomikos et al., 2013) and confirms the robustness of CVaR under leptokurtic conditions, as discussed in Sarykalin et al. (2008). Notably, hedged return distributions are different for long and short hedges in terms of asymmetry and kurtosis. This feature is effectively captured by the minimum CVaR hedging method, as opposed to symmetric hedging approaches. The estimated mean returns for short and long hedged portfolios for Capesize, Panamax and Supramax vessels are −0.0035, 0.0016, −0.0011, −0.0011, −0.0021 and 0.0003, respectively. Additionally, measures such as standard deviation, VaR_Deviation and CVaR_Deviation of are positively related to the vessel size – confirming existing literature that larger vessels typically exhibit greater freight rate volatility (e.g. Kavussanos, 1996).

Moreover, distributions of hedged returns appear to be less leptokurtic compared to the corresponding spot and FFA returns, suggesting that the minimum CVaR strategy effectively suppresses extreme return fluctuations. This is particularly valuable in the dry bulk freight sector, where fat-tailed distributions are prevalent due to the large and sudden price swings. In such environments, the minimum CVaR deviation approach demonstrates a clear advantage over traditional methods like rolling OLS and BGARCH which are not able to capture the asymmetries in the loss distribution. Conversely, when distributions of freight rate returns are close to normal, CVaR and variance-based strategies tend to yield similar results, as also observed by Rockafellar and Uryasev (2000).

[11] An extension for future research could be to move beyond pure risk minimization and integrate transaction costs such as bid-ask spreads, broker's commission, clearing fees, and margining requirements—whether through explicit cost-aware constraints, or through utility-based optimization—in order to better reflect the trade-offs faced by practitioners.

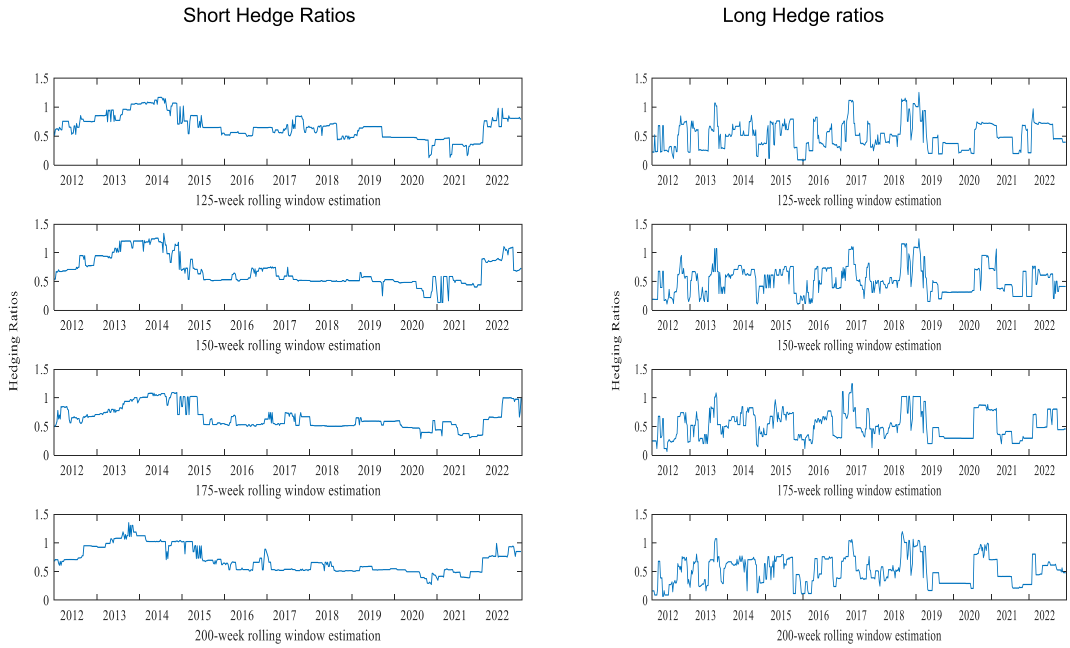

Fig. 6. Estimated CVaR hedge ratios using different size rolling windows for Capesize vessels
Notes: The figure illustrates the impact of varying the rolling window size (125, 150, 175 and 200 weeks) on the estimated Minimum CVaR Deviation hedge ratios for Capesize vessels. Hedge ratios are computed out-of-sample using weekly spot and 1-quarter ahead FFA returns over the period January 4, 2011 to December 23, 2022. While shorter windows capture local market dynamics more responsively, they introduce higher variability. The 150-week window balances responsiveness with stability.

5.4. Efficient frontiers of Buffered Probability of Exceedance (bPOE)

The minimum CVaR deviation hedging strategy aims to minimize the expected loss exceeding a specified confidence level. While CVaR effectively captures the magnitude of losses in the tail of the distribution, it does not explicitly quantify the probability of exceeding a particular loss threshold. To address this limitation, we incorporate the Buffered Probability of Exceedance (bPOE) - a probabilistic risk measure that provides a two-dimensional perspective on tail risk. The bPOE framework captures both the likelihood and the severity of extreme losses, thereby offering a more comprehensive view of downside risk compared to CVaR alone. The theoretical soundness and practical relevance of bPOE have been reinforced by recent developments in its optimization under uncertainty (Rockafellar and Uryasev, 2020).

Assuming an initial portfolio value of $1 million, to normalize results across vessel classes and make loss figures economically meaningful to be interpreted on a consistent dollar basis, and minimize the bPOE (i.e. the probability of expected losses on the tail of portfolio returns), subject to CVaR constraints across a range of confidence levels. By doing so, we generate an efficient frontier representing a set of Pareto-optimal combinations under uncertainty (see Shang et al., 2016). These frontiers reflect the trade-off characteristics that CVaR-based frameworks were originally designed to address (Rockafellar and Uryasev, 2000). The optimal probabilities of expected losses for the hedged portfolios bounded by corresponding loss thresholds are shown in Fig. 8. The shape of the efficient frontiers - estimated for six hedged portfolios (short and long hedges across Capesize, Panamax, and Supramax vessels) - reveals substantial variation in both exceedance probabilities and loss magnitudes. These differences highlight the need to account for vessel-specific risk profiles and hedge asymmetries when designing tail risk mitigation strategies. This empirical application also supports Mafusalov and Uryasev (2018), who demonstrate that bPOE enables nuanced portfolio-level differentiation between loss probability and severity across different asset classes.

To examine the trade-off between expected loss magnitude and its probability of occurrence, we construct a closed-form solution for each portfolio tracing the boundary of the efficient frontier, from the lowest to the highest expected loss levels. Each point on this frontier reflects the minimum achievable CVaR (i.e., potential loss magnitude) for a given level of bPOE (i.e., risk probability). This approach is particularly important in dry bulk risk management, where spot and FFA rates are highly volatile, and basis risk is pronounced. The efficient frontier illustrates how investors or hedgers can effectively manage the trade-off between risk magnitude and

Table 7
Out-of-sample performance of CVaR hedging strategies.

Capesize	Variance	Variance Reduction	HE	AVR	MAD	90 % VaR_Dev	90 % CVaR_Dev
Unhedged	0.0448	0.0188	41.96 %	−0.0036	0.1146	**0.2191**	0.3078
Short 125	0.0260						
Short 150	0.0258	0.0190	42.41 %	**−0.0030**	**0.1129**	0.2238	0.3044
Short 175	**0.0252**	**0.0196**	**43.75 %**	−0.0035	0.1137	0.2231	**0.3036**
Short 200	0.0254	0.0194	43.30 %	−0.0035	0.1207	0.2306	0.3179
Long 125	0.0246	0.0202	**45.10 %**	0.0015	0.1241	0.1898	0.2931
Long 150	0.0248	0.0200	44.64 %	**0.0099**	**0.1196**	0.1879	**0.2913**
Long 175	0.0251	0.0197	43.97 %	0.0016	0.1220	**0.1818**	0.2991
Long 200	0.0253	0.0195	43.53 %	0.0016	0.1207	0.1843	0.3065
Panamax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0119	0.0034	28.57 %	**−0.0006**	0.0813	0.1260	0.1727
Short 125	0.0085						
Short 150	**0.0084**	**0.0035**	**29.42 %**	−0.0012	**0.0778**	**0.1122**	**0.1646**
Short 175	0.0086	0.0033	27.73 %	−0.0012	0.0820	0.1178	0.1782
Short 200	0.0089	0.0030	25.21 %	−0.0010	0.0804	0.1162	0.1730
Long 125	0.0091	0.0028	23.52 %	−0.0012	0.0839	0.1235	0.1709
Long 150	0.0085	0.0034	**28.57 %**	−0.0010	**0.0776**	**0.1119**	**0.1638**
Long 175	0.0088	0.0031	26.05 %	**−0.0009**	0.0777	0.1286	0.1648
Long 200	0.0096	0.0023	19.32 %	**−0.0009**	0.0803	0.1323	0.1722
Supramax	**Variance**	**Variance Reduction**	**HE**	**AVR**	**MAD**	**90 % VaR_Dev**	**90 % CVaR_Dev**
Unhedged	0.0041	**0.0005**	**12.20 %**	−0.0025	0.0465	0.0566	0.1102
Short 125	**0.0036**						
Short 150	**0.0036**	**0.0005**	**12.20 %**	−0.0021	0.0469	0.0589	0.1062
Short 175	0.0037	0.0004	9.76 %	**−0.0020**	**0.0457**	**0.0559**	**0.1050**
Short 200	0.0038	0.0003	7.32 %	−0.0022	0.0471	0.0569	0.1103
Long 125	0.0035	0.0006	14.63 %	0.0002	0.0478	0.0565	0.1152
Long 150	0.0036	0.0005	12.20 %	0.0001	0.0464	0.0574	0.0963
Long 175	0.0035	0.0006	14.63 %	0.0002	**0.0457**	**0.0539**	**0.0950**
Long 200	**0.0034**	**0.0007**	**17.07 %**	**0.0003**	0.0465	0.0559	0.0975

The out-of-sample period for Capesize, Panamax, and Supramax spans from January 4, 2011 to December 28, 2022. The weekly sample is constructed using Wednesday price observations. HE represents the hedge effectiveness; AVR is the average value of hedged portfolio, MAD is mean absolute deviation; 90 % VaR_Dev is the value of VaR Deviation at the 90 % confidence level, and 90 % CVaR_Dev is the value of CVaR Deviation at the 90 % confidence level. Bold values indicate the best-performing hedging strategy for each vessel type under the respective metric. For the CVaR-based strategy, the long and short results are evaluated independently and highlighted in bold if they outperform all other strategies in their respective direction. If a symmetric strategy (e.g., OLS) provides the best overall performance, but the CVaR-hedge outperforms it in one direction only (long or short), both values are bolded to reflect the CVaR strategy's outperformance in one direction.

probability, offering a coherent framework for strategic decision-making under uncertainty.[12] Importantly, the shapes and slopes of the efficient frontiers differ between short and long hedging strategies and across vessel classes, reflecting heterogeneous tail risk profiles. The results show that Capesize vessels—for both long and short hedges—are associated with higher probabilities of large losses, whereas Panamax and Supramax vessels exhibit lower loss probabilities for both hedge directions. For instance, at the 90 % minimum bPOE, the CVaR for short hedging in Capesize market is $34,000, compared to $16,000 and $14,000 for short hedges in the cases of Panamax and Supramax vessels, respectively. These differences highlight the greater tail risk exposure faced by larger vessel classes and demonstrate the practical value of bPOE-based optimization in addressing such asymmetries.

A closer comparison of efficient frontiers for short and long hedges within each vessel category reveals notable asymmetries. At the 90 % minimum bPOE level, the CVaR values for short and long positions are relatively close. However, as the minimum bPOE declines – capturing more extreme tail events - the differences between efficient frontiers for short and long hedging increase considerably. For example, at the 50 % minimum bPOE level, the CVaR for Capesize short and long hedges are $135,000 and $100,000, respectively. Such discrepancies in estimated efficient frontiers stem from differences in the shapes of the distributions of hedged portfolio returns. Specifically, the distributions for short and long hedged portfolios are markedly distinct and different, highly non-normal with excess kurtosis and skewness, and change over time. This analysis further reinforces the importance of the minimum CVaR deviation strategy,

[12] Recent work on shipping freight market emphasizes the value of probabilistic models for improving forward-looking decision-making under uncertainty. For instance, Sel and Minner (2025) demonstrate that a probabilistic based forecast model and procurement strategy which incorporates FFA and spot freight rate uncertainty outperforms models based on point forecasts, reinforcing the growing emphasis on probabilistic risk-based optimization in maritime logistics.

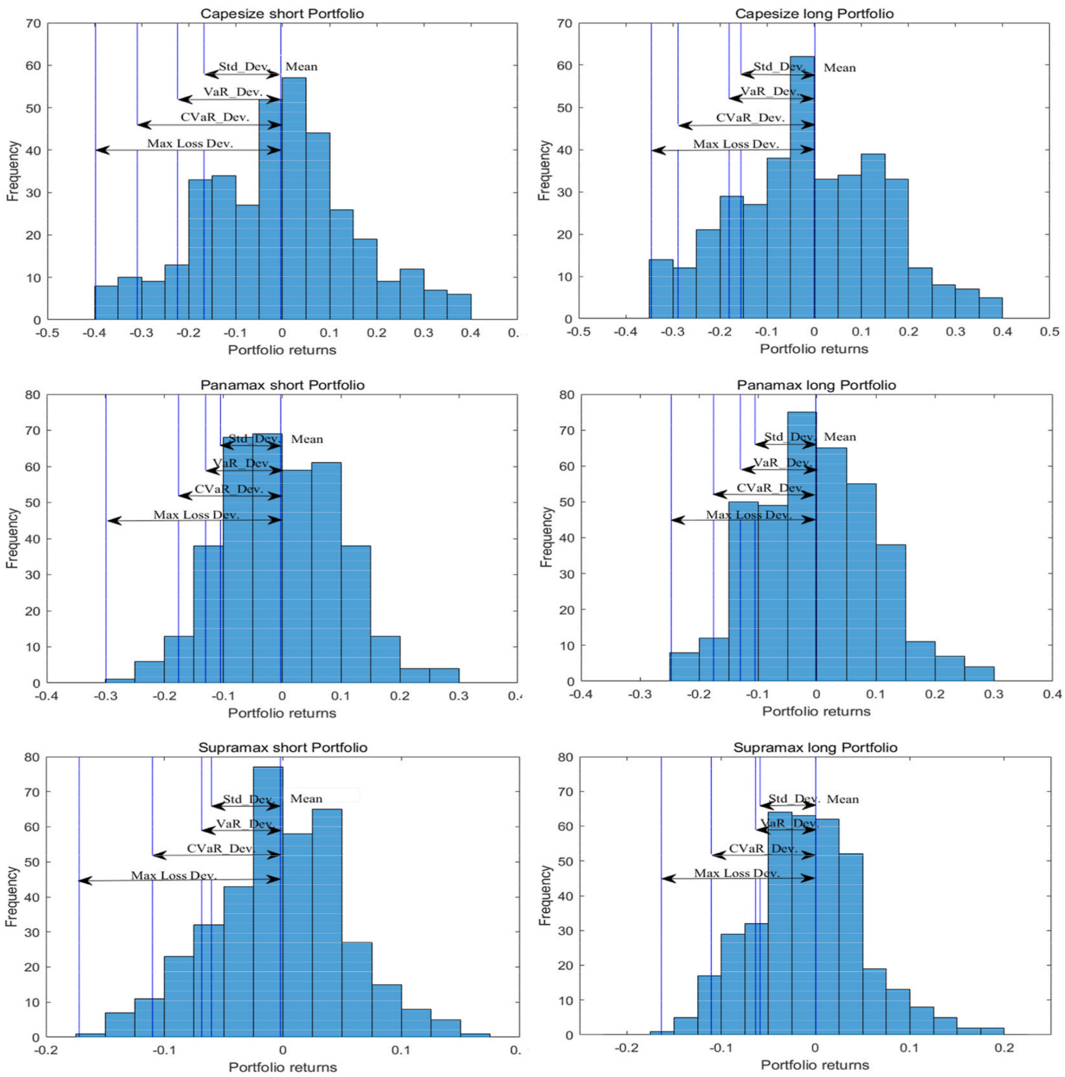

Fig. 7. Distribution of portfolio returns and graphical representation of different risk measures.

Notes: This figure presents empirical distributions of weekly portfolio returns of hedged positions, along with visual annotations for key risk measures. Mean is the average value of hedged portfolio returns; St Dev is the value of standard deviation; VaR Dev is the value of VaR Deviation at 90 % confidence level; CVaR Dev is the value of CVaR Deviation at 90 % confidence level; Max Loss Dev. is the maximum loss deviation.

which is explicitly designed to capture distributional asymmetries, making it a robust and targeted tool for hedging freight rate risk.

In practice, these results have direct implications for hedging decisions. CVaR–bPOE frontiers allow shipowners, charterers, and investors to select hedge ratios that best align with their risk appetite, balancing the probability and severity of extreme losses in line with corporate objectives. They therefore act as a practical decision-support tool, helping market participants translate complex tail-risk trade-offs into transparent hedging choices that support operational and financial planning in volatile freight markets.

5.5. Summary and key takeaways

Overall, the key takeaway is that CVaR-based hedging strategy reduces downside risk of shipping freight rates across vessel types, with particularly strong performance in the Capesize segment, which exhibits the highest inherent volatility and tail risk (Kavussanos and Visvikis, 2006; Alizadeh and Nomikos, 2009). The results also indicate that CVaR hedging approach is more appropriate for the determination of hedge ratios in dry bulk shipping where return distributions are highly non-normal with excess kurtosis and significant asymmetry. The CVaR hedging approach also yields a more stable dynamic hedge ratio compared to MRS and BGARCH models which reduces portfolio rebalancing costs. Moreover, estimation of bPOE further enhances risk control by directly assessing the tail probabilities and revealing the trade-off between loss likelihood and severity.

By vessel class, the main findings can be summarized as follows.

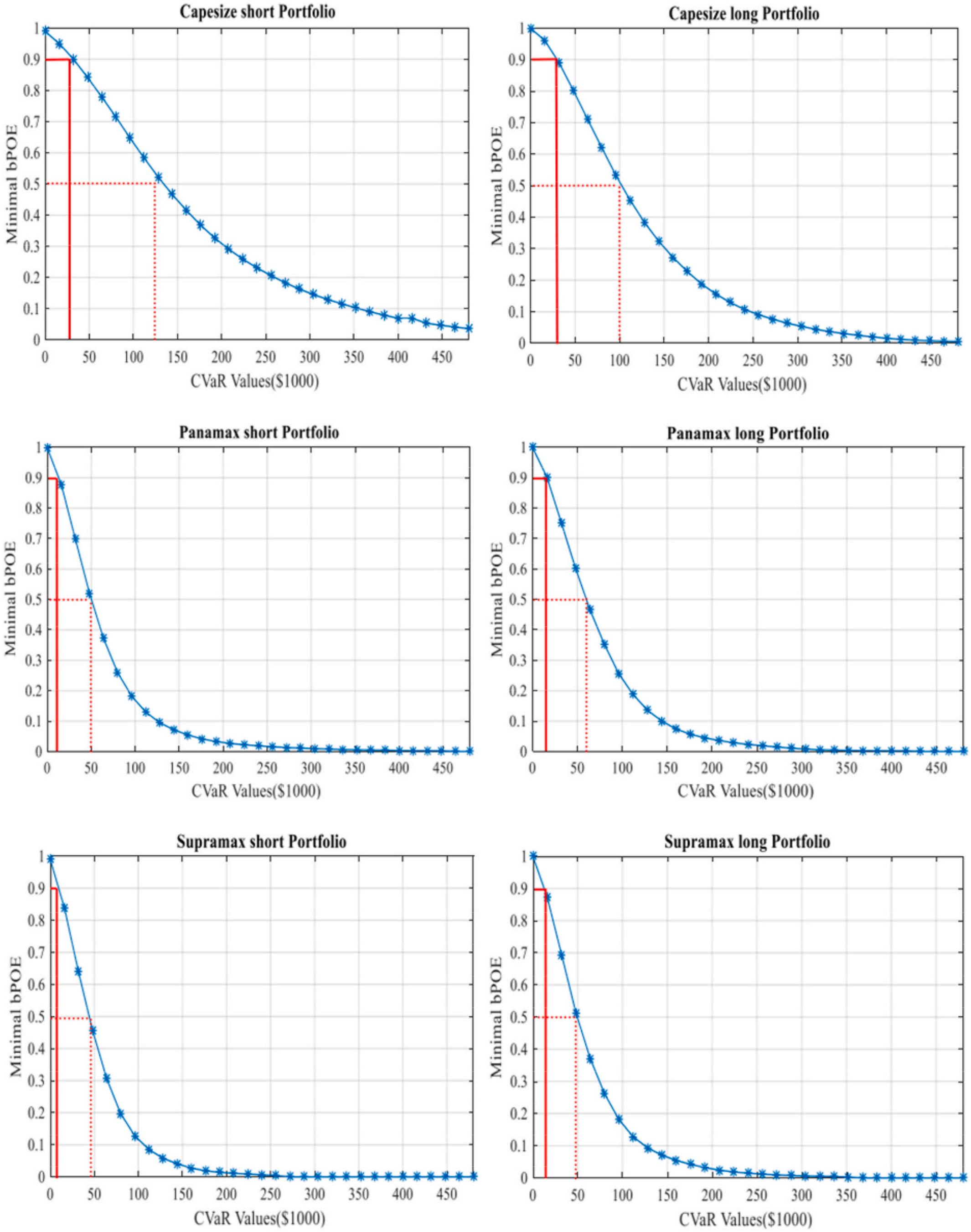

Fig. 8. Efficient frontier: bound on CVaR values vs minimal bPOE.
Notes: The figure illustrates the efficient frontiers for six hedged portfolios (long and short positions in Capesize, Panamax, and Supramax vessels), plotted as pairs of CVaR and bPOE values. Each point represents the trade-off between tail loss magnitude (CVaR) and tail exceedance probability (bPOE). The frontiers demonstrate portfolio-specific asymmetries and validate the suitability of bPOE as a complementary risk measure for freight rate hedging.

- In the Capesize market, static and dynamic CVaR hedging strategies achieve the greatest variance reduction, superior downside control, and more symmetric return distributions. The pronounced long/short asymmetry in the sector highlights the need for tailored risk management, as bPOE optimization reveals higher short-side tail probabilities.
- In the Panamax sector, the CVaR strategy achieves the highest variance reduction and slightly lower CVaR deviations for the short hedge position in out-of-sample tests. Although Rolling OLS hedging approach attains the lowest CVaR deviations in dynamic

settings, CVaR hedging strategies outperform GARCH-based models and provide more flexible downside risk control. Moreover, compared to the Capesize sector, Panamax freight rates exhibit moderate tail risk and some asymmetry, with short hedgers facing higher risk.

- In the Supramax sector, CVaR based hedging strategies seem to outperform benchmarks by lowering downside risk out-of-sample. While Supramax has the lowest tail risk and relatively symmetric long/short frontiers, CVaR and bPOE approaches still improve risk management, particularly where traditional methods fall short.

The superior performance of the CVaR-based hedging framework can be explained by its explicit focus on downside risk and its alignment with practitioners' asymmetric loss aversion - rather than simply minimizing overall variance. CVaR hedging strategy allows for long and short hedge ratios to be different, explicitly controls extreme loss probabilities, and handles the heavy-tailed, skewed, and regime-sensitive return distributions typical of shipping markets (Kavussanos and Visvikis, 2010; Tsouknidis, 2016; Goswami et al., 2023). It is also dynamically responsive to changes in higher moments and robust to structural breaks and time-varying basis risk (Cao et al., 2010; Alizadeh et al., 2015). Unlike variance-based approaches reflecting quadratic utility, CVaR better matches practitioners' loss-averse preferences, further enhancing its practical effectiveness (Rockafellar and Uryasev, 2000; Melnikov and Smirnov, 2012; Shrestha et al., 2018). These combined features allow CVaR-based strategies to deliver superior risk protection in volatile, non-normal shipping markets.

6. Conclusions

A key challenge for participants in the dry bulk shipping market lies in managing extreme volatility and the imperfect co-movement between spot freight rates and their corresponding FFAs. In addition, the return distributions of both spot and FFA returns show marked deviations from normality, including asymmetry, excess kurtosis, and high levels of basis risk (Sun et al., 2019), all of which adversely affect the performance of traditional hedging strategies. To address these limitations, we propose a new hedging strategy based on minimum CVaR deviation, offering a tail-sensitive approach suitable for general, non-normal loss distributions.

We evaluate the performance of the minimum CVaR deviation strategy against several benchmarks, including the naïve, OLS, Bivariate GARCH and MRS-GARCH hedging models, all grounded in the minimum variance principles. Empirical results, based on traditional variance reduction, average value of hedged portfolio returns, and various deviation measures, demonstrate that the CVaR-based strategy consistently delivers superior hedging performance in the dry bulk market. The naïve approach exhibits the lowest hedging effectiveness and is particularly unsuitable due to substantial basis risk. Under heavy-tailed return distributions, the minimum CVaR deviation approach clearly outperforms the minimum variance strategy. In contrast, when return distributions are approximately normal, the minimum CVaR and minimum variance hedging strategies exhibit similar levels of effectiveness in terms of variance reduction. Notably, the hedge ratios derived from the CVaR approach are relatively more stable over time, requiring fewer rebalancing adjustments, thereby lowering transaction costs in dynamic settings. Results across multiple hedging effectiveness measures in-sample and out-of-sample further reinforce the consistency and reliability of these findings.

More importantly, the efficient frontier generated by minimizing bPOE subject to CVaR constraints facilitates a meaningful trade-off between the probability and the magnitude of expected losses. This bivariate risk perspective bridges theoretical optimization and real-world risk management. The findings of this study are particularly relevant to stakeholders in the shipping industry, including shipowners, charterers, portfolio managers and derivative traders offering a robust framework for managing freight rate exposure. The proposed methodology provides valuable guidance for managing freight rate risk and a structured framework for tailoring hedging strategies to different levels of risk tolerance and loss probabilities. Future research could extend this framework by explicitly incorporating transaction costs, liquidity constraints, and margining requirements to better reflect the realities of freight trading. In practice, wider adoption of CVaR–bPOE approaches will depend on overcoming challenges related to data quality, computational demands, and industry acceptance beyond variance-based benchmarks.

CRediT authorship contribution statement

Xiaolin Sun: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Amir H. Alizadeh:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Panos K. Pouliasis:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

Albrecht, P., Huggenberger, M., Pekelis, A., 2012. VaR and CVaR minimal futures hedging strategies: an analytical approach. SSRN Electron. J. 1–18.
Alizadeh, A.H., Huang, C.Y., van Dellen, S., 2015. A regime switching approach for hedging tanker shipping freight rates. Energy Econ. 49, 44–59.
Alizadeh, A.H., Nomikos, N.K., 2009. Shipping Derivatives and Risk Management. Palgrave Macmillan.
Byers, J.W., Popova, I., Simkins, B.J., 2021. Robust estimation of conditional risk measures using machine learning algorithm for commodity futures prices in the presence of outliers. Journal of Commodity Markets 24, 100174.
Cao, M., Conlon, T., 2023. Composite jet fuel cross hedging. Journal of Commodity Markets 30, 100271.
Cao, Z., Harris, R.D., Shen, J., 2010. Hedging and Value-at-Risk: a semi-parametric approach. J. Futures Mark. 30 (8), 780–794.
Davis, J.R., Uryasev, S., 2016. Analysis of tropical storm damage using Buffered Probability of Exceedance. Nat. Hazards 83 (1), 465–483.
Ederington, L.H., 1979. The hedging performance of the new futures markets. J. Finance 34 (1), 157–170.
Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50 (4), 987–1007.
Goswami, A., Karali, B., Adjemian, M.K., 2023. Hedging with futures during nonconvergence in commodity markets. Journal of Commodity Markets 32, 100364.
Harris, R.D., Shen, J., 2006. Hedging and Value-at-Risk. J. Futures Mark. 26 (4), 369–390.
Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Econ. Lett. 6 (3), 255–259.
Johnson, L., 1960. The theory of hedging and speculation in commodity futures. Rev. Econ. Stud. 27 (3), 139–151.
Kavussanos, M.G., 1996. Comparisons of volatility in the dry-cargo ship sector. Spot versus time-charters, and smaller versus larger vessels. J. Transport Econ. Pol. 30 (1), 67–82.
Kavussanos, M.G., Nomikos, N.K., 2000. Futures hedging when the structure of the underlying asset changes: the case of the BIFFEX contract. J. Futures Mark. 20 (8), 775–801.
Kavussanos, M.G., Visvikis, I.D., 2004. Market interactions in returns and volatilities between spot and forward shipping freight markets. J. Bank. Finance 28 (8), 2015–2049.
Kavussanos, M.G., Visvikis, I.D., 2006. The price risk of different vessel sizes in the dry bulk sector. Transport. Res. E Logist. Transport. Rev. 42, 435–456.
Kavussanos, M.G., Visvikis, I.D., 2010. The hedging performance of the capesize forward freight market. In: Cullinane, K. (Ed.), International Handbook of Maritime Economics and Business. Edward Elgar Publishing.
Krokhmal, P., Palmquist, J., Uryasev, S., 2002. Portfolio optimization with conditional Value-at-Risk objective and constraints. J. Risk 4 (2), 43–68.
Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financ. Quant. Anal. 28 (4), 535–551.
Ljung, G.M., Box, G.E., 1978. On a measure of lack of fit in time series models. Biometrika 65 (2), 297–303.
Mafusalov, A., Uryasev, S., 2018. Buffered Probability of Exceedance: mathematical properties and optimization algorithms. SIAM J. Optim. 28 (2), 1077–1103.
Mafusalov, A., Shapiro, A., Uryasev, S., 2018. Estimation and asymptotics for Buffered Probability of Exceedance. Eur. J. Oper. Res. 270 (3), 826–836.
Melnikov, A., Smirnov, I., 2012. Dynamic hedging of conditional Value-at-Risk. Insur. Math. Econ. 51 (1), 182–190.
Nomikos, N.K., Kyriakou, I., Papapostolou, N.C., Pouliasis, P.K., 2013. Freight options: price modelling and empirical analysis. Transport. Res. E Logist. Transport. Rev. 51, 82–94.
Norton, M., Mafusalov, A., Uryasev, S., 2017. Soft margin support vector classification as buffered probability minimization. J. Mach. Learn. Res. 18 (1), 2285–2327.
Pavlikov, P., Uryasev, S., 2014. CVaR norm and applications in optimization. Optimization Letters 8, 1999–2020.
Rockafellar, R.T., Royset, J.O., 2010. On buffered failure probability in design and optimization of structures. Reliab. Eng. Syst. Saf. 95 (5), 499–510.
Rockafellar, R.T., Uryasev, S., 2000. Optimization of conditional Value-at-Risk. J. Risk 2 (3), 21–41.
Rockafellar, R.T., Uryasev, S., 2002. Conditional Value-at-Risk for general loss distributions. J. Bank. Finance 26 (7), 1443–1471.
Rockafellar, R.T., Uryasev, S., 2013. The fundamental risk quadrangle in risk management, optimization and statistical estimation. Surveys in Operations Research and Management Science 18 (1–2), 33–53.
Rockafellar, R.T., Royset, J.O., 2018. Superquantile/CVaR risk measures: second order theory. Ann. Oper. Res. 262, 3–28.
Rockafellar, R.T., Uryasev, S., 2020. Minimizing Buffered Probability of Exceedance by progressive hedging. Math. Program. 181, 453–472.
Sarykalin, S., Serraino, G., Uryasev, S., 2008. Value-at-Risk vs. Conditional Value-at-Risk in risk management and optimization. In: State-of-the-art Decision-Making Tools in the Information-Intensive Age. INFORMS.
Sel, B., Minner, S., 2025. Probabilistic forecast-based procurement in seaborne forward freight markets under demand and price uncertainty. Transport. Res. E Logist. Transport. Rev. 193, 103830.
Shang, D., Kuzmenko, V., Uryasev, S., 2016. Cash flow matching with risks controlled by Buffered Probability of Exceedance and conditional Value-at-Risk. Ann. Oper. Res. 260, 501–514.
Shrestha, K., Subramaniam, R., Peranginangin, Y., Philip, S.S.S., 2018. Quantile hedge ratio for energy markets. Energy Econ. 71, 253–272.
Souhir, B.A., Heni, B., Lotfi, B., 2019. Price risk and hedging strategies in Nord Pool electricity market evidence with sector indexes. Energy Econ. 80, 635–655.
Stein, J.L., 1961. The simultaneous determination of spot and futures prices. Am. Econ. Rev. 51, 1012–1025.
Stopford, M., 2009. Maritime Economics, third ed. Routledge, London.
Sukcharoen, K., Leatham, D.J., 2017. Hedging downside risk of oil refineries: a vine copula approach. Energy Econ. 66, 493–507.
Sun, X., Liu, H., Zheng, S., Chen, S., 2018. Combination hedging strategies for crude oil and dry bulk freight rates on the impacts of dynamic cross-market interaction. Marit. Pol. Manag. 45 (2), 174–196.
Sun, X., Haralambides, H., Liu, H., 2019. Dynamic spillover effects among derivative markets in tanker shipping. Transport. Res. E Logist. Transport. Rev. 122, 384–409.
Tsouknidis, D.A., 2016. Dynamic volatility spillovers across shipping freight markets. Transport. Res. E Logist. Transport. Rev. 91, 90–111.
Wang, Y., Wu, C., Yang, L., 2015. Hedging with Futures: does anything beat the naïve hedging strategy? Manag. Sci. 61 (12), 2870–2889.
Yang, J., Ge, Y.-E., Li, K.-X., 2022. Measuring volatility spillover effects in dry bulk shipping market. Transp. Policy 125, 37–47.

Further reading

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74 (366), 427–431.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? J. Econom. 54 (1–3), 159–178.
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346.