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Marine fuel hedging under the sulfur cap regulations[☆]

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ABSTRACT

This paper examines the hedging potential of crude oil financial derivatives in the marine industry and concentrates on the dependence between marine fuels and crude oil futures. We argue that marine fuel consumers and producers can reduce uncertainty regarding their portfolios under environmental regulations aimed at air pollution reduction. Our results show that uncertainty can be reduced up to 72%. In addition, we find that complex dynamic hedging strategies do not provide significant benefits compared to the static method, and asymmetries in dependence structures are not driving the results. We also identify Gasoil and Brent Crude futures as the universal hedging instruments to manage uncertainty across the global ports.

1. Introduction

The marine fuel[1] price accounts for up to 60% of the overall transportation costs of a cargo carried by marine vessels (Wang and Teo, 2013). It is also estimated that the cost of transportation represents, on average, 15% of the value of imported goods (UNCTAD, 2017). Therefore, the expenditures associated with marine fuels represent a considerable part of the final price of the globally shipped goods. Any distortion that causes an increase in the price of marine fuels, thus, inevitably raises the price of these goods. Since more than 80% of internationally traded goods are shipped via sea (UNCTAD, 2017), the uncertainty regarding fuel prices negatively impacts consumers purchasing imported goods and the overall level of consumption, the inherent part of the gross domestic product. While consumers would benefit from any reduction in this uncertainty, they cannot reduce it by themselves. In contrast, marine fuel consumers/producers can reduce bunker price uncertainty through active hedging of their spot positions with a reward of stabilized cash flows. Our paper shows that hedging spot exposure by futures contracts is effective under the strict environmental regulations known as “IMO 2020” introduced by the International Maritime Organization (IMO).[2]

The need for environmentally friendly transport stems from the fact that shipping is one of the main contributors to air pollution. According to IGU (2017), one large container ship using bunker fuel with 3% sulfur content emits as much sulfur oxides as 50 million diesel-burning cars. To mitigate these negative impacts, the IMO issued fuel regulations that reduce the sulfur emissions in fuels from the current level of 3.5% to 0.5%. Cutting the sulfur content in fuels has been an urgent issue for a considerable amount of time,[3] and the IMO hopes for a 77% drop in overall sulfur oxide emissions from ships. Due to its broad impact,[4] the IMO 2020 regulation is thought to be one of the major challenges of the modern era.

There are currently three paths to compliance with the IMO 2020 regulation that are constantly being revisited to detect the most economically efficient candidate. The first method consists of installing scrubbers, i.e., an exhaust gas cleaning system that removes sulfur from postcombustion exhaust emissions, in conjunction with the usage of heavy-sulfur fuel oils (HSFOs). The second option to meet the low-sulfur requirements is to switch from HSFOs to low-sulfur fuel oils

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1 The historical term for fuels used in the shipping and marine sectors is bunker fuel, and we use it in our work interchangeably.
2 IMO is a specialized agency of the United Nations that is responsible for the safety, security and ecological protection measures of shipping on a global scale.
3 Efforts to limit the harmful impact of ship emissions date back to 1973 when the Marine Pollution Convention (MARPOL) was adopted.
4 Restrictions affect the marine and shipping industries, as well as other energy segments, redefining crude oil market dynamics in general. They also pose a challenge to producers, physical traders, crude oil refining companies, etc.

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(LSFOs),[5] such as marine gasoil (MGO). Conversion to alternative fuels is the third compliance path — due to their early development in ports and the impossibility of combining alternative fuels with old watercraft, such a method is not the object of this paper's interest.

This paper stresses the importance of hedging spot bunker positions because marine fuels take up to 7% of the crude oil barrel (Halff et al., 2019) and are significantly affected by oil price fluctuations. By hedging, companies lock in the price and shield their portfolios against potential adverse price movements in the markets. The literature focuses mainly on optimal hedging strategies represented by the minimum variance hedge ratio (MVHR).[6] The traditional estimation of MVHR is carried out via ordinary least squares (OLS) regression (Ederington, 1979); however, this method has been criticized by Myers and Thompson (1989) because it cannot capture the maximum information available when the hedging decision is made. As a result, a more flexible mechanism accounting for (asymmetric) time-varying volatility from (multivariate) generalized autoregressive conditional heteroscedasticity (GARCH) models was formulated (Myers, 1991; Lien and Yang, 2008; Adams and Gerner, 2012; Cifarelli and Paladino, 2015). This approach also has critics, who argue that a more accurate volatility estimation does not always translate into better performance from the risk-minimizing standpoint beyond OLS (Ku et al., 2007; Ji and Fan, 2011). Moreover, Lien et al. (2002) discuss the trade-off between the benefits of a dynamic hedge and the costs of portfolio rebalancing, and Lien (2009) contend that GARCH-based and random coefficient models produce excessively volatile MVHR, which leads to unnecessary transaction costs. Motivated by the possible nonexistence of a corresponding futures contract, the concept of cross-hedging[7] has been developed — in the absence of a derivative contract on the asset whose price is being hedged, the hedger should choose a derivative contract of a similar asset to the underlying.

Marine fuel hedging is not a new issue in the literature. Among others, Menachov and Dicer (2001) and Alizadeh et al. (2004) concentrate on the use of standardized oil futures contracts for hedge construction. The work of Alizadeh et al. (2004) demonstrates a variance reduction of 43% in hedging bunker prices in Rotterdam by using the weekly Brent futures traded on Intercontinental Exchange (ICE). Our work follows this strand of literature[8] as it allows us to concentrate on both the supply and demand side of the marine fuel industry. To be specific, oil futures contracts can be used to hedge the demand of shipping companies as well as the supply of oil producers and bunker fuels providers. Moreover, this approach leads to a straightforward comparison of the hedging effectiveness of the IMO 2020 compatible fuels without making additional assumptions regarding shipping routes, cargo quantity, vessel type etc. In addition to oil futures hedging strategy we have used the freight price proxied by Baltic Dry Index to hedge marine fuels. Overall, the hedging effectiveness of this approach is almost zero/negative, and we do not present the full results of this analysis in the main text.[9]

Our results indicate that highly liquid oil futures contracts traded on the New York Mercantile Exchange (NYMEX) and ICE effectively mitigate marine fuel price uncertainty. To remain in compliance with the IMO 2020 regulation and following Panasiuk and Turkina (2015), Chu-Van et al. (2019), and Zhu et al. (2020), we analyze dependencies between two types of bunker fuels, i.e., heavy and low sulfur fuel oils, and various oil futures contracts. We rely on three strands of hedge construction — naïve hedge, the standard OLS approach and multivariate GARCH (MGARCH) models. Alternative strategies are compared via rolling window out-of-sample forecasting exercises, allowing for new market information arrival and flexible adjustment.

We document that low sulfur bunker fuels can be hedged with oil futures contracts, resulting in a variance reduction up to 71.94% on a weekly basis and almost 21.88% on a daily basis. We obtain slightly worse performance for a high sulfur alternative, i.e., 51%/15.5% for a weekly/daily hedging horizon. The hedging effectiveness measured by variance reduction reveals that complex dynamic hedging strategies do not provide significant benefits compared to the static approach, and we have not detected substantial asymmetric effects in the spot-futures commodity pairs. Our results also indicate that Gasoil and Brent futures should be used for hedging purposes in the bunker industry, notwithstanding the local conditions at the different ports used in our study.

2. Data and methodology

Our empirical analysis is based on spot and futures energy commodity contracts obtained from three separate sources. The NYMEX futures contracts were extracted from the U.S. Energy Information Administration, and we analyze the West Texas Intermediate Crude Oil (WTI), which is considered to be the global benchmark in oil pricing, No. 2 heating oil traded as New York Harbor ultra-low sulfur No. 2 diesel (ULSD), and reformulated blendstock for oxygenate blending gasoline (RBOB). The European complements were collected from the ICE Market data, and we consider North Sea Brent, the European counterpart to WTI, and Gasoil, the ICE benchmark in low sulfur futures. The spot contracts were retrieved from the Bix Bunker Index, and we collect data from Rotterdam, Singapore, Fujairah and Houston, which are four key bunkering ports that together cover approximately 25% of global bunker volumes (Ship & Bunker, 2020). We study intermediate fuel oil 380 (IFO), the most widely used high-sulfur fuel, and low-sulfur MGO.

Our data set is quoted in U.S. dollars and consists of the daily closing prices from April 2, 2008 until March 30, 2020. We explicitly exclude all observations that fall on weekends, U.S. federal holidays and some state holidays[10] according to the trading schedule of each exchange. In addition, some values that are missing in the respective time series due to different exchanges and port operations are replaced by the preceding day's values. Our final dataset consists of 3062 trading days. For ease of empirical analysis, we transform closing prices into continuously compounded return series and define them as

$$r_{i,t} = 100 * \ln \frac{P_{i,t}}{P_{i,t-1}},$$

where $r_{i,t}$ represents the log-returns of commodity i at time t, $P_{i,t}$ denotes the closing price of commodity i at time t and $P_{i,t-1}$ is the corresponding lagged closing price. Basic descriptive statistics for the

[5] Low-sulfur oils are generally considered to contain 1% of sulfur and, thus, do not comply with the IMO. However, for ease of reporting, the abbreviation LSFOs stands for fuels compliant with the regulations.

[6] The other hedging strategies include hedge ratios based on expected utility maximization (Cecchetti et al., 1988), the mean extended-Gini coefficient (Kolb and Okunev, 1992), value-at-risk (Hung et al., 2006; Cao et al., 2010), and generalized semivariance (Lien and Tse, 2000).

[7] Some papers use the term proxy and cross hedging interchangeably.

[8] Besides fuel hedging, it is possible to hedge also the freight price or the value of the vessel using various over-the-counter (OTC) traded financial derivatives. Among others, Samitas and Tsakalos (2010) investigate the effectiveness of freight forward agreements (FFAs) during financial crises and measure their impacts on shipping firms' value, and Adland et al. (2020) argue that the hedging efficiency is greater for newer vessels up to fifteen years of age and that the static hedging ratio is better than the dynamic hedging ratio. In contrast to oil-futures hedge, the disadvantage of OTC derivative-based hedging strategies is the lack of liquidity and transparency. Moreover, the freight price/vessel value hedge does not allow us to study the impact of the transition to the IMO 2020 compliant fuels. Therefore we do not consider this way of hedging in our work.

[9] Detailed results are available from authors upon request.

[10] Martin Luther King Jr. Day, President's Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, Christmas Day, and New Year's Day.

data are included in Table 5 in Appendix A. We use a rolling window with a fixed length of 1250 observations, i.e., five years, for estimation and forecasting purposes.

The simplest hedging strategy we employ in our work is the naïve hedge. It represents minimizing the exposure in that the investor who is long in the spot should sell the unit of futures contracts and repurchase them when she sells the spot, i.e., one-to-one hedge. If the prices between these two markets change by the same amount, the investor's net position remains unchanged, resulting in a perfect hedge (Myers, 1991). In commodity markets, the perfect hedge is a purely theoretical concept since it is infeasible[11] under normal conditions to (cross) hedge 100% of the respective asset. It is worth noting that the majority of the studies on financial time series ascertain that any type of hedge is more effective than a naked exposure.

2.1. Optimal hedge ratio

The optimal hedge ratio (OHR) λ, also known as the minimum variance hedge ratio (Johnson, 1960), is defined as the ratio of the covariance between the underlying spot and futures returns to the variance of futures returns, i.e., as follows:

$$\lambda = \frac{\mathrm{cov}(s,f)}{\mathrm{var}(f)}, \tag{1}$$

where λ is the risk-minimizing hedge ratio, s denotes the return of the spot position and f is the return of the futures position.

Let r_t^H be the return of the hedged portfolio defined as follows:

$$r_t^H = s_t - \lambda_t f_t, \tag{2}$$

where λ_t is the number of futures contracts the hedger must sell/buy for each unit of the spot asset bought/sold. The OHR can therefore be viewed as the proportion of the long (short) spot position that is covered by futures sales (purchases) (Cifarelli and Paladino, 2015).

The conditional variance in Eq. (2) is given as follows:

$$\mathrm{var}(r_t^H \mid \Omega_{t-1}) = \mathrm{var}(s_t \mid \Omega_{t-1}) + \lambda_t^2 \mathrm{var}(f_t \mid \Omega_{t-1}) - 2\lambda_t \mathrm{cov}(s_t, f_t \mid \Omega_{t-1}), \tag{3}$$

where Ω_{t-1} is the information set available at time $t-1$, $\mathrm{cov}(s_t, f_t \mid \Omega_{t-1})$ denotes the conditional covariance between spot and futures returns, and $\mathrm{var}(f_t \mid \Omega_{t-1})$ is the conditional variance of futures returns. Johnson (1960) demonstrates that the OHR is equal to the value of r_t^H minimizing the conditional variance of the hedged portfolio returns on the given information set, as follows:[12]

$$\lambda_t^* = \arg\min_{\lambda_t} \mathrm{var}(r_t^H \mid \Omega_{t-1}). \tag{4}$$

It is worth noting that if futures returns are martingale processes and spot and futures returns are jointly normal, the optimal hedge ratio from any hedging strategy converges to the minimum variance hedge ratio (Cifarelli and Paladino, 2015).

In our analysis, we start with the standard econometric practice for cross hedging, the OLS method. In the simplest case, the unconditional (static) hedge ratio is based on the model proposed by Ederington (1979). A linear relationship between returns is given as follows:

$$s_t = \mu + \lambda f_t + u_t, \quad u_t \overset{iid}{\sim} N(0, \sigma^2), \tag{5}$$

where μ and λ are the regression parameters. The OLS estimate of the coefficient on f_t is the time t optimal unconditional hedge ratio estimator λ_t^*. In our empirical analysis, we calculate the OHR for each period with a fixed window length. We, therefore, obtain a series of unconditional OHRs.

Within the context of multivariate GARCH (MGARCH) models, Baillie and Myers (1991) and Kroner and Sultan (1993) note that the optimal time-varying conditional hedge ratio can be written as follows:

$$\lambda_{t|\Omega_{t-1}}^* = \frac{\mathrm{cov}(s_t, f_t \mid \Omega_{t-1})}{\mathrm{var}(f_t \mid \Omega_{t-1})}. \tag{6}$$

We obtain the inputs for Eq. (6) using the (asymmetric) dynamic conditional correlation ((A)DCC) GARCH model of Engle (2002) and Cappiello et al. (2006). Similar to Pan et al. (2014), we filter the univariate time series by an autoregressive process of order one prior to application of the (A)DCC-GARCH models. The (A)DCC-GARCH used in our work is defined as follows:

$$H_t = D_t R_t D_t,$$

where D_t is a diagonal matrix of conditional time varying standard deviations and $D_t = diag\left(\sqrt{h_{i,t}}\right)$ and $h_{i,t}$ are univariate GARCH processes. We rely on the standard GARCH(1,1) of Bollerslev (1986), i.e. $h_{i,t} = \omega_i + \alpha_i r_{i,t-1}^2 + \beta_i h_{i,t-1}$, and the GJR-GARCH(1,1,1) of Glosten et al. (1993), which account for asymmetry in returns, i.e., $h_{i,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \gamma_i \epsilon_{i,t-1}^2 I_{i,t-1} + \beta_i h_{i,t-1}$, where $I_{i,t-1} = 1$ if $\epsilon_{i,t-1} < 0$, and zero otherwise.

The dynamics of the correlation matrix are given by the transformation

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

where for DCC:

$$Q_t = (1 - A - B)\bar{Q} + A\left(\epsilon_{t-1}\epsilon_{t-1}^T\right) + BQ_{t-1}$$

and for ADCC:

$$Q_t = (1 - A - B)\bar{Q} - G\bar{M} + A\left(\epsilon_{t-1}\epsilon_{t-1}^T\right) + BQ_{t-1} + Gm_{t-1}m_{t-1}^T,$$

with $\bar{Q} = E(\epsilon_{t-1}\epsilon_{t-1}^T)$ being the unconditional covariance matrix of the standardized residuals from the univariate GARCH processes, $Q_t^* = diag\left(\sqrt{q_{11,t}}, \dots, \sqrt{q_{nn,t}}\right)$, $\bar{M} = E(m_{t-1}m_{t-1}^T)$ and $m_t = I(r_t < 0) \odot r_t$, with $I[\cdot]$ being an $n \times 1$ indicator function that takes on the value of 1 if the argument is true, and 0 otherwise, and $\odot$ refers to the Hadamard product, i.e. element-by-element multiplication.

2.2. Hedging performance measures

One of the most widely used criteria for evaluating the hedging effects for different models is the hedging effectiveness index (HEI) derived by Ederington (1979). The HEI assesses the extent to which changes in the value of the futures returns offset changes in the value of the spot returns. By construction, the higher positive values of the HEI indicate a better hedging approach that leads to a greater risk reduction. The measure of relative performance improvements is represented by the percentage variance reduction, which is given as follows:

$$HEI = 1 - \frac{\mathrm{var}(r_t^H)}{\mathrm{var}(r_t^U)}, \tag{7}$$

where $\mathrm{var}(r_t^H)$ denotes the variance of the returns to a hedged portfolio and $\mathrm{var}(r_t^U)$ is the variance of the returns to an unhedged portfolio on the spot market.

Our analysis also provides a statistical comparison of the forecasting performance of the competing models. To compare the predictive accuracy of the forecasts obtained from the respective models, we perform a standard Diebold–Mariano test (Diebold and Mariano, 1995). The statistical significance of apparent predictive superiority relies on the loss differential $d_{ij,t}$, which is defined as follows:

$$d_{ij,t} = \ell_{i,t} - \ell_{j,t},$$

[11] According to Hull (2014), the investor might not be sure of the exact date the asset will be bought or sold. In addition, there may be a requirement for the futures contract to be closed out before its delivery month. Market expectations and the cost of carry are equally important to consider. For these reasons, a perfect hedge is rare.

[12] To derive the OHR at time t conditional on the information available at $t-1$, it is necessary to take the partial derivative of Eq. (3) with respect to λ_t, set it equal to zero and solve for λ_t.

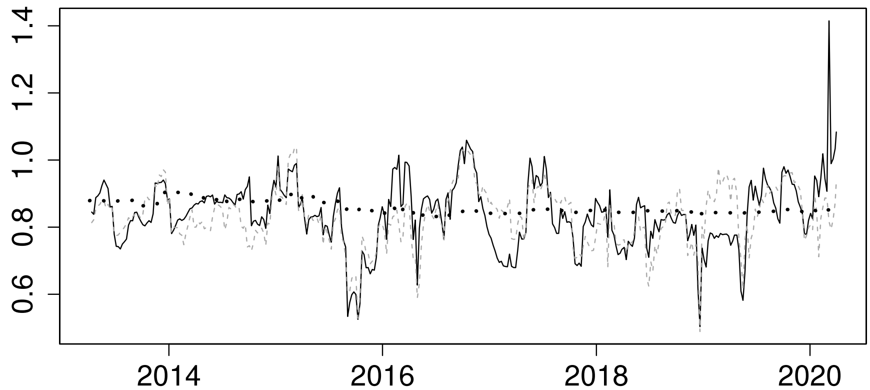

Fig. 1. Weekly Rotterdam MGO - GASOIL optimal hedge ratios. Note: The OHRs from DCC are the solid black line, those from ADCC are the dashed dark gray line and those from OLS are the black dotted line.

where $\ell_{i,t}$ and $\ell_{j,t}$ are loss functions of the *i* and *j* models, respectively, at time *t*. The individual loss function is of the following form:

$$\ell_{i,t} = \left(s_t - \lambda_{i,t} f_t\right),$$

and the null hypothesis of $\ell_{i,t} = \ell_{j,t}$ says that the expected losses of both models are equal.

3. Empirical analysis and discussion of results

In this section, we present the results of our empirical analysis. Specifically, we investigate the hedging effectiveness of energy commodities and try to identify the best hedging instrument and a reasonable hedging strategy. Furthermore, we address differences across regional spot markets.

3.1. The out-of-sample evidence — weekly data

We start discussing our results with a hedge duration equivalent to one week. Such a setup is the industry standard because the effects of the daily price fluctuations in the volatile markets are moderated in the longer horizon. The weekly data used in our analysis are a subset of our daily dataset and consist of the end-of-week prices.

Let us now comment on the out-of-sample hedging effectiveness presented in Table 1. We start with the naïve hedge, the simplest method employed in our paper. In all but two cases, a one-to-one hedge of the IFO contracts reduces the variance to some extent, as seen in the upper part of Table 1. Importantly, for specific spot-futures pairs (e.g., Rotterdam IFO - ULSD), it provides higher variance reduction than (A)DCC models; however, the naïve hedge does not show the best performance in any of the cases. Concentrating on the MGO contracts, the RBOB futures show the worst performance in all ports. In Fujairah, the naïve approach massively increases the variance notwithstanding the futures used for hedging. In the remaining ports, the situation is as follows: the naïve hedge reduces the variance when all but the RBOB futures are used in Rotterdam and Singapore, while in Houston, the WTI and BRENT futures increase the variance to some extent.

Moving to the OLS- and MGARCH-based hedging strategies, the Rotterdam bunkers show the greatest hedging effectiveness across all four ports, giving a slight preference to LSFOs. The best risk reduction of 71.94% can be attained when the Rotterdam MGO spot contract forms a pair with Gasoil futures. In contrast, the lowest effectiveness is achieved once RBOB is included. This is valid worldwide and supported by daily data analysis in a similar manner. Singapore bunkers also advocate that the LSFO alternative may be more beneficial if added into the portfolio to minimize risks as much as 60.42%. Next, the hedging performance for the port of Fujairah results in a variance reduction ranging from 14.06% to 37.48%. In contrast to Rotterdam and Singapore, a better hedging performance is achieved using high sulfur fuel. The hedging performance on Houston spot contracts does not clearly favor LSFOs or HSFOs. For the low sulfur option, the HEI takes values from 26.12% to 42.61%, whereas it varies between 25.91% and 42.02% in the case of the heavy sulfur alternative. Overall, the best performance in terms of variance reduction is achieved by the standard OLS method.

Thus far, we have presented the overall performance of the models. As is customary in the literature, we also provide a pairwise comparison of the predictive accuracy using a standard Diebold–Mariano test. The results are presented in Table 2, where we compare the naïve hedging strategy to the OLS/DCC/ADCC models in Panel A.1/A.2/A.3, the OLS-based hedge to the DCC/ADCC models in Panel B.1/B.2, and DCC to ADCC in Panel C.

Panels A.1-A.3 of Table 2 show that for low sulfur fuel the naïve hedge strategy is outperformed in almost all spot-futures pairs by all competing models. In the high sulfur alternative, a one-to-one hedge is always dominated by the OLS and (A)DCC models when RBOB is used as the hedging instrument. Interestingly, OLS is the only method that is never outperformed by naïve hedges. In contrast, a naïve hedge is preferred when (A)DCC models are combined with the ULSD futures in Rotterdam and Houston. Panels B.1-B.2 of Table 2 show that in the majority of cases, OLS outperforms the MGARCH models and, hence, yields greater protection against risk exposure. We must stress here that while for some spot-futures pairs, the difference in hedging effectiveness is relatively small, e.g., Singapore MGO - Gasoil 60.42% OLS vs. 58.94% ADCC variance reduction, for other pairs (e.g., Houston IFO - WTI), there is a difference of almost 12 percentage points. Finally, Panel C indicates the similar performances of the symmetric and asymmetric DCC models.

As has already been indicated, dynamic models may induce greater variance while forming portfolios. Allowing for time variation across the entire variance–covariance matrix of returns, the hedge ratios are too sensitive to the size and sign of the change in prices as a consequence of information arrival. Furthermore, multivariate conditional correlation models require a sufficient time frame, thereby allowing us to infer particular features of our time series accordingly. Reducing the number of observations in the case of weekly data may play a significant role in identifying a more flexible model for bunker hedging since there might be a problem with the convergence behavior and the efficiency of the optimization of MGARCH models. Despite the clear advantages of the (A)DCC models and their justification in the field of correlation modeling, it becomes obvious that the relatively simple OLS method is on a comparable level, if not better, from the standpoint of risk diversification. It is more or less stable and not as volatile as its advanced counterparts; see Fig. 1. This is sensible from the perspective

Table 1
Out-of-sample hedging effectiveness — weekly horizon.

		IFO									
		WTI		ULSD		RBOB		BRENT		GASOIL	
		Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI
Rotterdam											
	Unhedged	29.07	–	29.07	–	29.07	–	29.07	–	29.07	–
	Naïve	18.33	36.83	17.31	40.33	26.97	*7.04*	14.72	49.27	14.36	50.49
	OLS	16.41	**43.46**	16.81	**42.06**	20.16	**30.51**	14.13	**51.32**	14.33	**50.62**
	DCC	18.19	37.42	19.09	34.35	22.42	22.88	15.35	47.19	15.18	*47.80*
	ADCC	18.66	*35.81*	19.19	*33.98*	21.05	27.62	15.46	*46.84*	15.05	48.23
Singapore											
	Unhedged	24.81	–	24.81	–	24.81	–	24.81	–	24.81	–
	Naïve	20.59	*16.80*	17.58	28.95	28.13	*−13.65*	16.74	*32.34*	14.85	*40.01*
	OLS	16.31	**34.11**	16.19	**34.57**	18.56	**25.00**	14.59	**41.06**	14.33	**42.11**
	DCC	17.55	29.27	18.27	*26.37*	18.92	23.75	15.16	38.91	14.64	40.97
	ADCC	17.82	28.17	18.14	26.86	18.84	24.06	15.33	38.21	14.80	40.33
Fujairah											
	Unhedged	25.96	–	25.96	–	25.96	–	25.96	–	25.96	–
	Naïve	23.94	*7.58*	20.32	21.55	32.90	*−27.01*	19.70	*23.92*	16.88	34.83
	OLS	18.62	**28.12**	18.54	**28.41**	21.05	**18.72**	16.92	**34.66**	16.19	**37.48**
	DCC	19.91	23.29	20.28	21.87	22.26	14.27	17.94	30.89	16.80	35.29
	ADCC	20.79	19.91	20.54	*20.86*	22.14	14.71	18.51	28.69	17.21	*33.72*
Houston											
	Unhedged	32.62	–	32.62	–	32.62	–	32.62	–	32.62	–
	Naïve	24.31	25.30	22.66	30.38	31.38	*3.58*	21.54	33.83	19.00	41.62
	OLS	21.53	**33.84**	21.64	**33.50**	24.11	**25.91**	20.11	**38.21**	18.87	**42.02**
	DCC	24.88	23.71	24.23	25.72	27.64	15.25	22.69	*30.45*	20.28	*37.83*
	ADCC	25.48	*21.88*	24.30	*25.50*	26.23	19.57	22.53	30.92	20.22	38.00
		MGO									
		WTI		ULSD		RBOB		BRENT		GASOIL	
		Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI
Rotterdam											
	Unhedged	16.40	–	16.40	–	16.40	–	16.40	–	16.40	–
	Naïve	11.57	*29.33*	7.43	54.63	19.69	*−20.26*	8.69	*46.89*	4.86	70.33
	OLS	7.68	**53.10**	6.60	**59.68**	10.37	**36.63**	6.53	**60.09**	4.59	**71.94**
	DCC	8.27	49.59	7.71	*53.00*	10.81	34.09	6.92	57.83	5.03	*69.35*
	ADCC	8.05	50.90	7.41	54.85	10.44	36.32	6.91	57.88	4.93	69.93
Singapore											
	Unhedged	14.31	–	14.31	–	14.31	–	14.31	–	14.31	–
	Naïve	13.53	*5.23*	9.68	*32.17*	21.21	*−48.54*	10.79	*24.42*	6.69	*53.15*
	OLS	7.80	**45.34**	7.57	**46.98**	9.72	**31.93**	7.05	**50.61**	5.65	**60.42**
	DCC	8.53	40.39	8.44	41.03	10.38	27.47	7.39	48.34	5.98	58.24
	ADCC	8.39	41.38	8.11	43.35	10.16	28.97	7.34	48.72	5.88	58.94
Fujairah											
	Unhedged	3.57	–	3.57	–	3.57	–	3.57	–	3.57	–
	Naïve	19.60	*−449.64*	14.07	*−294.60*	25.97	*−628.46*	17.02	*−377.50*	13.31	*−273.45*
	OLS	2.89	**18.86**	3.08	13.54	3.05	**14.56**	2.82	**20.83**	3.03	**15.01**
	DCC	2.91	18.55	3.11	12.77	3.42	4.27	2.83	20.64	3.07	14.13
	ADCC	2.97	16.94	3.07	**14.06**	3.37	5.50	2.84	20.53	3.07	13.94
Houston											
	Unhedged	14.90	–	14.90	–	14.90	–	14.90	–	14.90	–
	Naïve	16.84	*−13.29*	11.67	*21.51*	23.46	*−57.8*	15.22	*−2.39*	10.60	*28.72*
	OLS	9.78	**34.22**	9.01	**39.40**	11.01	25.94	9.68	**34.90**	8.53	**42.61**
	DCC	10.27	31.10	9.75	34.58	11.03	26.02	10.17	31.76	9.04	39.37
	ADCC	10.07	32.44	9.58	35.73	11.01	**26.12**	9.84	33.97	8.70	41.62

Note: The panels are structured according to spot contract specifications and display percentage values of portfolio variance and HEI (hedging effectiveness index). The best/worst hedging performances for individual bunkers are reported in bold/italics.

of transaction costs since portfolio rebalancing would not need to be executed weekly.

3.2. Robustness check — daily data

In this section, we provide the results of the robustness check when daily data are used for the analysis. Although the higher frequency of the data is not standard for marine fuel hedging, it might provide us with valuable information regarding the nature of the time series dynamics. Using the daily data for estimation, we also address an issue regarding the sufficient length of data from the previous section. The results with the out-of-sample hedging effectiveness are presented in Table 3. For the purpose of reporting, the variances are rounded up to two decimal points, which is why they sometimes completely coincide in terms of the static and dynamic models, but the reduction may differ to some degree. The results of the pairwise comparison are presented in Table 4, where we compare the OLS to the DCC/ADCC models in Panel A.1/A.2 and the DCC to ADCC in Panel B. We do not display the comparison of the naïve hedging strategy because it was always dominated by the other models.

The most discernible characteristic of more granulated data is that the hedging effectiveness altogether declines for any combination of commodities. Our results are in line with previous literature which, demonstrates decreasing hedging effectiveness with decreasing hedging

Table 2
Pair-wise forecasting accuracy comparison — weekly horizon.

		IFO					MGO				
		WTI	ULSD	RBOB	BRENT	GASOIL	WTI	ULSD	RBOB	BRENT	GASOIL
Panel A.1											
	Rotterdam	**1.49***	0.63	**2.24*****	1.18	0.16	**2.88*****	**1.37***	**3.15*****	**3.66*****	**1.69****
	Singapore	**2.05****	**1.52***	**2.58*****	**2.40*****	1.23	**3.30*****	**2.18*****	**3.22*****	**4.26*****	**2.71*****
	Fujairah	**1.81****	**1.76****	**2.32*****	**2.15****	**1.49***	**6.31*****	**7.11*****	**4.35*****	**6.63*****	**7.84*****
	Houston	**1.87****	1.08	**2.54*****	**1.61****	0.40	**5.25*****	**2.89*****	**4.58*****	**4.66*****	**3.34*****
Panel A.2											
	Rotterdam	0.13	*−1.87***	**1.67****	−0.67	−1.11	**2.85*****	−0.84	**3.01*****	**2.67*****	−0.66
	Singapore	**1.92****	−0.81	**2.32*****	**1.60***	0.44	**3.61*****	**1.84****	**3.15*****	**4.02*****	**1.83****
	Fujairah	**1.37***	0.09	**2.09****	1.04	0.15	**6.36*****	**7.31*****	**4.47*****	**6.73*****	**8.14*****
	Houston	−0.43	*−2.16***	**1.75****	−0.74	*−2.09***	**4.67*****	**2.24*****	**4.53*****	**3.91*****	**1.97****
Panel A.3											
	Rotterdam	−0.16	*−1.70***	**2.09****	−0.65	−0.75	**2.52*****	0.07	**3.11*****	**2.66*****	−0.27
	Singapore	**1.50***	−0.61	**2.35*****	**1.37***	0.12	**3.11*****	**2.32*****	**3.21*****	**3.96*****	**2.22*****
	Fujairah	1.06	−0.17	**2.01****	0.69	−0.33	**6.38*****	**7.27*****	**4.43*****	**6.71*****	**8.09*****
	Houston	−0.71	*−1.64***	**2.42*****	−0.59	*−1.48**	**5.06*****	**2.51*****	**4.65*****	**4.40*****	**2.73*****
Panel B.1											
	Rotterdam	*−2.02***	*−1.52**	−1.25	*−1.43**	−1.11	*−2.18****	*−1.96***	*−1.32**	*−1.77***	*−2.23****
	Singapore	*−1.54**	*−1.44**	−0.30	−0.93	−0.43	*−1.74***	*−1.63***	*−1.89***	*−2.26****	−1.14
	Fujairah	*−1.62***	*−1.65***	*−1.34**	−1.09	−0.85	−0.01	−0.11	−1.21	0.05	−0.15
	Houston	*−2.59****	*−2.20****	*−1.99***	*−1.99***	*−2.04***	*−2.17***	*−2.54****	−0.03	*−1.87***	*−2.16***
Panel B.2											
	Rotterdam	*−1.71***	*−1.47**	−0.68	−1.25	−0.77	*−1.97***	*−1.91***	−0.17	*−1.52**	*−2.14***
	Singapore	*−1.78***	*−1.37**	−0.21	−1.07	−0.64	*−2.66****	*−1.36**	−1.07	*−1.48**	*−1.74***
	Fujairah	*−2.02***	*−1.56**	−1.00	*−1.47**	−1.23	−0.58	0.26	*−1.31**	−0.03	−0.26
	Houston	*−2.40****	*−2.26****	*−1.70***	*−1.63***	*−1.64***	*−1.71***	*−2.25****	0.06	−0.88	−0.85
Panel C											
	Rotterdam	−0.64	−0.18	**1.82****	−0.30	0.28	0.75	1.09	**2.97*****	0.09	0.52
	Singapore	−0.69	0.30	0.30	−0.94	−0.70	0.41	1.09	**1.70****	0.41	0.45
	Fujairah	*−2.11***	−0.50	0.27	*−1.98***	*−1.34**	*−1.66***	0.68	0.55	−0.21	−0.33
	Houston	−1.08	−0.11	**1.70****	0.39	0.13	1.12	0.97	0.11	**1.84****	**1.52***

Note: Panels A.1/A.2/A.3 report comparisons of the naïve (benchmark) and OLS/DCC/ADCC GARCH models. Panel B.1/B.2 report comparisons of the OLS (benchmark) and DCC/ADCC GARCH models. Panel C reports comparisons of the DCC (benchmark) and ADCC GARCH models. For each spot-futures pair, we report the Diebold–Mariano test statistics — significantly more/less accurate forecasts with respect to the benchmark model are in bold/italics; significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

horizon.[13] In our case, the naïve hedging strategy has the most striking change in performance. The naïve approach massively increases the variance for all but one pair (Rotterdam IFO - Gasoil) and could be regarded as a rather unreliable technique. In such a case, institutions are better off if their portfolios are completely unhedged.

Moving to the remaining types of hedging, a close inspection of Rotterdam bunkers indicates a slight preference for the LSFOs. The best hedging effectiveness can be achieved using MGO spots with Gasoil, in which a reduction in risk by as much as 21.88% is reached. For the rest of the Rotterdam spot — future pairs, the reduction is lower than 10%. Overall, the Rotterdam fuels show the highest hedging efficiency in both HSFO and LSFO fuels. Singapore spot contracts do not appear to give any significant preferential treatment concerning low- and heavy-sulfur alternatives — the WTI, ULSD and Brent futures are better alternatives to hedge the IFO contract, while RBOB and Gasoil are better for hedging MGO. Similar to Rotterdam, the highest hedging effectiveness is obtained in the MGO-Gasoil pair with a variance reduction of 13.44%, thus slightly favoring LSFOs. The hedging effectiveness patterns for Fujairah port are different than those for Rotterdam and Singapore. The LSFO fuel represented by MGO shows the least potential for cross-hedging – the maximum variance reduction, which is achieved by RBOB, is only 1.68%. Our analysis of Fujairah contracts narrowly supports the choice of HSFOs in terms of the variance reduction, which is as much as 8.05% obtained from the OLS model. Using Houston spot contracts, we obtain similar results as in Fujairah; i.e., HFSOs generally provide higher variance reduction than LSFOs, although the highest reduction is achieved by the MGO-Gasoil pair. Overall, across the ports, Gasoil is the most effective hedging futures contract, followed by Brent and WTI, which have similar performances. The RBOB seems to be the least effective contract.

Regarding the statistical comparison of the hedging strategies, Panel A of Table 4 displays similar forecasting performances for the OLS and (A)DCC models in the majority of spot-futures pairs. The (A)DCC performs better than OLS in Singapore, Fujairah and Houston when WTI is used for cross hedging. In contrast, OLS outperforms (A) DCC when Gasoil is used to hedge MGO in Rotterdam and IFO in Fujairah. In Panel B, there is no apparent difference in hedging effectiveness between the symmetric MGARCH model and its asymmetric equivalent. As both of the models are computationally demanding in the same way, there is no clear winner in this respect. Visual inspection of the optimal hedge ratios of the Rotterdam MGO-GASOIL cross-hedge, i.e., the spot-futures pair with the highest variance reduction, displayed in Fig. 2, reveals the possible benefits of using an OLS-based strategy. The OLS approach produces more stable, less volatile hedging ratios that might translate into lower transaction costs.

3.3. To hedge, or not to hedge

We have shown in our main analysis that the low sulfur fuels provide better hedging potential compared to their high sulfur counterparts, i.e almost 72% vs. nearly 51.5% variance reduction for MGO

[13] Among others, Merrick (1988) demonstrate that weekly hedging effectiveness of the S&P 500 futures is superior to daily hedge, Chen et al. (2004) using nine hedging horizons and 25 commodities find that hedging effectiveness increases with the length of the hedging horizon, Lien and Shrestha (2007) observe that as the hedging horizon increases, the performance of wavelet hedge ratio improves and Dewally and Marriott (2008) document increasing hedging effectiveness with increasing hedging horizon in base metal markets. The possible sources of differences of hedging performance are discussed in Wang et al. (2015).

Table 3
Out-of-sample hedging effectiveness — daily horizon.

		IFO									
		WTI		ULSD		RBOB		BRENT		GASOIL	
		Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI
Rotterdam											
	Unhedged	6.19	–	6.19	–	6.19	–	6.19	–	6.19	–
	Naïve	8.55	*−38.10*	7.53	*−21.62*	10.78	*−74.15*	7.74	*−25.04*	5.96	*3.68*
	OLS	5.64	8.83	5.78	6.63	5.92	4.42	5.61	9.32	5.24	**15.35**
	DCC	5.57	**9.98**	5.73	7.43	5.89	4.77	5.58	**9.84**	5.28	14.67
	ADCC	5.60	9.60	5.72	**7.54**	5.89	**4.91**	5.62	9.22	5.28	14.65
Singapore											
	Unhedged	5.96	–	5.96	–	5.96	–	5.96	–	5.96	–
	Naïve	9.28	*−55.77*	7.86	*−31.99*	11.06	*−85.69*	8.17	*−37.17*	6.33	*−6.35*
	OLS	5.68	4.57	5.71	4.07	5.78	3.04	5.60	6.03	5.31	**10.89**
	DCC	5.58	6.26	5.66	5.03	5.72	3.89	5.54	7.00	5.36	9.95
	ADCC	5.55	**6.81**	5.55	**6.76**	5.72	**3.99**	5.46	**8.41**	5.39	9.47
Fujairah											
	Unhedged	6.50	–	6.50	–	6.50	–	6.50	–	6.50	–
	Naïve	9.82	*−50.99*	8.37	*−28.68*	11.40	*−75.38*	8.84	*−36.03*	7.16	*−10.10*
	OLS	6.24	4.00	6.25	3.82	6.29	3.27	6.19	4.84	5.98	**8.05**
	DCC	6.15	**5.43**	6.22	**4.28**	6.27	**3.61**	6.15	**5.46**	6.08	6.56
	ADCC	6.18	5.00	6.24	3.95	6.29	3.27	6.18	4.92	6.09	6.33
Houston											
	Unhedged	7.42	–	7.42	–	7.42	–	7.42	–	7.42	–
	Naïve	10.85	*−46.19*	9.55	*−28.72*	12.80	*−72.45*	9.83	*−32.49*	8.45	*−13.93*
	OLS	7.22	2.70	7.29	1.70	7.31	1.47	7.17	3.38	7.08	**4.55**
	DCC	7.13	**3.90**	7.28	**1.91**	7.24	2.40	7.08	**4.61**	7.13	3.96
	ADCC	7.19	3.15	7.31	1.53	7.19	**3.09**	7.17	3.34	7.13	3.86
		MGO									
		WTI		ULSD		RBOB		BRENT		GASOIL	
		Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI	Variance	HEI
Rotterdam											
	Unhedged	3.57	–	3.57	–	3.57	–	3.57	–	3.57	–
	Naïve	7.10	*−98.75*	5.40	*−51.37*	9.08	*−154.46*	6.06	*−69.75*	3.68	*−3.01*
	OLS	3.33	6.72	3.32	7.05	3.45	3.40	3.28	**8.10**	2.79	**21.88**
	DCC	3.34	6.46	3.32	7.09	3.43	**3.90**	3.29	7.72	2.87	19.54
	ADCC	3.31	**7.16**	3.31	**7.40**	3.44	3.73	3.28	7.99	2.87	19.59
Singapore											
	Unhedged	3.08	–	3.08	–	3.08	–	3.08	–	3.08	–
	Naïve	7.42	*−140.72*	5.43	*−76.01*	8.64	*−180.04*	6.26	*−102.87*	4.07	*−32.13*
	OLS	2.99	3.15	2.94	4.70	2.96	4.01	2.94	4.81	2.67	**13.44**
	DCC	2.99	3.20	2.92	5.19	2.94	**4.68**	2.93	4.92	2.69	12.90
	ADCC	2.97	**3.55**	2.92	**5.26**	2.94	4.52	2.92	**5.31**	2.69	12.70
Fujairah											
	Unhedged	1.22	–	1.22	–	1.22	–	1.22	–	1.22	–
	Naïve	6.80	*−458.19*	4.60	*−277.47*	7.97	*−554.26*	5.69	*−367.21*	4.22	*−246.58*
	OLS	1.22	0.05	1.21	**0.99**	1.20	1.65	1.21	0.80	1.21	0.44
	DCC	1.21	**0.73**	1.21	0.48	1.20	**1.68**	1.21	**1.03**	1.21	0.63
	ADCC	1.22	0.24	1.22	−0.57	1.20	1.24	1.21	0.74	1.21	**0.65**
Houston											
	Unhedged	2.95	–	2.95	–	2.95	–	2.95	–	2.95	–
	Naïve	8.03	*−171.77*	5.96	*−101.70*	9.66	*−227.15*	6.93	*−134.52*	4.87	*−64.90*
	OLS	2.97	−0.61	2.96	−0.19	2.96	−0.29	2.96	−0.18	2.85	3.37
	DCC	2.89	**2.11**	2.91	**1.61**	2.92	1.04	2.88	**2.49**	2.84	4.02
	ADCC	2.90	1.73	2.91	1.47	2.91	**1.55**	2.89	2.24	2.81	**4.84**

Note: The panels are structured according to spot contract specifications and display the percentage values of portfolio variance and HEI (hedging effectiveness index). The best/worst hedging performances for individual bunkers are reported in bold/italics.

and IFO respectively. This feature could be observed in every port, and a clear preference for cross-hedges can be observed in the hedging effectiveness analysis. Moreover, the hedging performance of the IFO is in line with Alizadeh et al. (2004) - the best performing contract is Brent with almost 51.5% variance reduction (43% in Alizadeh et al. (2004)). In contrast, when we concentrate on a robustness check where daily data were employed, it is questionable whether lower values, particularly around 10% of the HEI, are appealing to companies or whether other methods of risk protection could be more attractive in the bunker market. In general, variance reductions ranging up to 20% for the positive outcome are mostly deemed ineffective (Maghyereh et al., 2017).

The order of the futures from the most to the least efficient is as follows: Gasoil; Brent with WTI alternating; ULSD and RBOB. This result suggests that the persistence in the transfer of information between spot and futures markets is one of the strongest for crude oil financial derivatives. Moreover, it can favorably be compared to Wang and Wu (2012), who assert that conventional or reformulated gasoline prices could be regarded as the most volatile commodities. As opposed to Lim and Turner (2016) and Pan et al. (2014), our results do not confirm that ULSD is usually the best cross hedge in energy markets. Moreover, our conclusions do not agree with the proposition of Chang et al. (2011) that the WTI specification displays greater efficacy in risk protection than Brent crude oil. However, it is well established in the literature

Table 4
Pair-wise forecasting accuracy comparison — daily horizon.

		IFO					MGO				
		WTI	ULSD	RBOB	BRENT	GASOIL	WTI	ULSD	RBOB	BRENT	GASOIL
Panel A.1											
	Rotterdam	0.85	0.64	0.34	0.37	−0.48	−0.31	0.03	0.52	−0.46	*−1.79***
	Singapore	**1.56***	0.79	1.24	0.95	−0.59	0.08	0.72	1.13	0.19	−0.62
	Fujairah	**1.70****	0.69	0.60	1.00	*−1.48**	0.53	−0.54	0.09	0.62	0.42
	Houston	0.88	0.18	0.99	1.09	−0.44	**1.66****	1.13	1.02	**1.59***	0.48
Panel A.2											
	Rotterdam	0.52	0.71	0.54	−0.07	−0.44	0.66	0.39	0.36	−0.22	*−1.85***
	Singapore	**1.99****	**1.50***	1.14	**1.56***	−1.01	0.54	0.58	0.81	0.72	−0.89
	Fujairah	1.04	0.23	0.00	0.12	*−1.49**	0.13	−0.94	−0.57	−0.03	0.53
	Houston	0.45	−0.14	**1.41***	−0.05	−0.58	**1.41***	1.01	**1.43***	**1.42***	1.16
Panel B											
	Rotterdam	−0.98	0.20	0.42	*−1.34**	−0.05	**1.61****	0.67	−0.40	0.31	0.09
	Singapore	0.69	**1.53***	0.32	**1.34***	−0.75	1.10	0.18	−0.68	0.95	−0.51
	Fujairah	*−1.39**	−0.77	*−1.40**	*−1.49**	−0.46	−1.21	−1.01	−1.11	−0.40	0.13
	Houston	−0.86	−1.25	1.21	*−1.96***	−0.16	*−1.62***	−0.71	0.67	*−1.48**	1.09

Note: Panel A.1/A.2 report the comparison of the OLS(benchmark) and DCC/ADCC GARCH models. Panel B reports the comparison of the DCC(benchmark) and ADCC GARCH models. For each spot-futures pair, we report the Diebold–Mariano test statistics — the significantly more/less accurate forecasts with respect to the benchmark model are in bold/italics; significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

Table 5
Descriptive statistics of daily returns.

		Mean	Max	Min	St. Dev.	Skewness	Kurtosis
	WTI	−0.05	21.36	−28.22	2.57	−0.59	14.42
	ULSD	−0.03	10.41	−19.75	2.04	−0.53	7.30
	RBOB	−0.05	21.66	−38.42	2.69	−1.53	25.16
	BRENT	−0.05	13.64	−27.58	2.30	−0.62	10.75
	GASOIL	−0.04	12.09	−14.00	1.90	−0.02	5.02
Rotterdam							
	IFO	−0.04	18.10	−25.05	2.40	−0.45	10.86
	MGO	−0.04	10.35	−20.72	1.87	−0.26	7.02
Singapore							
	IFO	−0.03	15.58	−27.56	2.30	−0.66	11.86
	MGO	−0.04	11.06	−20.76	1.73	−0.65	10.34
Fujairah							
	IFO	−0.03	14.02	−27.63	2.32	−0.68	12.16
	MGO	−0.02	10.05	−9.93	1.04	−0.72	14.25
Houston							
	IFO	−0.03	20.39	−25.39	2.45	−0.02	10.09
	MGO	−0.03	8.89	−10.22	1.76	−0.14	4.31

Note: The values for the mean, maximum, minimum and standard deviation are displayed in %.

Table 6
Unconditional correlations between OHR from DCC and ADCC GARCH.

	Weekly Data									
	IFO					MGO				
	WTI	ULSD	RBOB	BRENT	GASOIL	WTI	ULSD	RBOB	BRENT	GASOIL
Rotterdam	0.9189	0.9224	0.9448	0.9221	0.9153	0.9016	0.8268	0.9431	0.7423	0.6604
Singapore	0.9356	0.9508	0.9623	0.9480	0.9465	0.9133	0.8956	0.9379	0.7979	0.8357
Fujairah	0.9361	0.9389	0.9561	0.9477	0.9497	0.9264	0.9418	0.9569	0.9338	0.9424
Houston	0.8889	0.8900	0.9076	0.8885	0.9057	0.7178	0.738	0.8605	0.8206	0.7830
	Daily Data									
	IFO					MGO				
	WTI	ULSD	RBOB	BRENT	GASOIL	WTI	ULSD	RBOB	BRENT	GASOIL
Rotterdam	0.9686	0.9663	0.9702	0.9720	0.9599	0.9350	0.9163	0.9306	0.8835	0.8644
Singapore	0.9670	0.9552	0.9481	0.9595	0.9512	0.8926	0.8607	0.8682	0.8229	0.8489
Fujairah	0.9629	0.9545	0.9643	0.9685	0.9390	0.9076	0.7940	0.7868	0.9088	0.9639
Houston	0.9455	0.9801	0.9413	0.9553	0.9727	0.9850	0.9877	0.9670	0.9903	0.9708

Note: The table displays the unconditional correlations between the optimal hedge ratios from DCC and ADCC GARCH models.

that there are limited hedging opportunities owing to the absence of a proper derivatives market that would sufficiently offset the risk of price movement in the spot market (Basher and Sadorsky, 2016; Maghyereh et al., 2017).

Further attention is centered on different ports. We have demonstrated that the local conditions influence the degree of hedging effectiveness but not the chosen derivatives. As is usually assumed in the bunker industry, we confirm that ICE contracts are generally more convenient than NYMEX energy futures. Moreover, different local conditions prevent the uncomplicated pricing of mainly low sulfur options (Stefanakos and Schinas, 2014).

Our paper also contends that the sensitivity of hedging ratios to the asymmetry phenomenon is not supported by our data. The visual comparison of the optimal hedge ratios from the DCC and ADCC

Table 7
Yearly DM comparison: DCC vs. ADCC GARCH.

		Weekly Data															
		IFO								MGO							
		2013	2014	2015	2016	2017	2018	2019	2020	2013	2014	2015	2016	2017	2018	2019	2020
Rotterdam																	
	WTI	−0.55	−1.23	−0.55	0.93	0.28	0.79	−1.1	0.14	0.42	−0.7	0.18	0.72	−0.73	−0.05	−0.18	0.75
	ULSD	−2.77***	−0.62	0.15	1.19	−0.02	−0.6	0.52	−1.12	0.93	0.01	1.26	0.32	−0.11	−1.05	0.61	0.55
	RBOB	−1.39*	0.48	0.89	1.77**	−0.65	0.99	0.65	−1.44*	−0.53	1.64**	1.07	2.33***	0.73	0.42	−0.43	1.35*
	BRENT	−0.94	−0.83	0.67	0.99	0.31	−0.76	−0.02	−0.93	−0.15	−0.13	1.11	2.21**	−0.9	−1.01	−0.47	−0.18
	GASOIL	−2.83***	−0.93	−0.05	1.40*	0.45	−0.33	0.28	−0.77	1.63*	0.15	0.19	0.99	0.42	−1.07	0.66	0.09
Singapore																	
	WTI	−0.37	0.78	−0.32	−0.39	−0.58	−0.48	−1.86**	0.09	0.71	−0.96	−0.8	−0.08	1.05	−0.11	0.48	0.59
	ULSD	−2.68***	0.62	0.95	0.15	−1.54*	−0.84	−2.00**	0.29	2.19**	0.18	0.56	−1.02	1.24	−0.79	0.87	1.14
	RBOB	0.22	0.91	0.81	1.68**	−0.77	−1.16	−0.7	−1.23	1.13	0.23	0.33	1.73**	0.14	0.18	1.50*	0.91
	BRENT	0.22	−0.22	0.3	1.17	−1.34*	−0.17	−1.32*	−0.94	1.39*	−0.77	−0.67	0.61	0.45	−0.79	1.67**	−0.14
	GASOIL	−3.01***	−0.35	−0.06	1.39*	−0.3	−0.22	−1.71**	−0.26	2.29***	−1.49*	−0.49	0.75	0.55	−0.75	0.31	0.29
Fujairah																	
	WTI	0.8	−1.33*	0.22	−0.5	0.5	0.04	−2.11**	−1.95**	1.99**	−1.05	−1.05	−1.08	−0.07	−1.2	1.33*	−0.65
	ULSD	−1.46*	0.75	−0.18	0.01	−0.29	−0.12	−1.59*	−0.14	2.46***	0.57	−1.18	−0.4	−0.33	0.46	−0.76	1.02
	RBOB	0.11	0.61	0.04	0.5	−0.91	−0.35	−0.58	0.28	−1.30*	0.13	−2.23***	−0.5	−1.13	−1.02	−1.25	1.17
	BRENT	1.87**	−0.56	0.67	0	−0.38	−0.26	−1.53*	−2.13**	1.24	0.1	−0.08	−0.8	1.33*	−0.63	1.96**	0.01
	GASOIL	−2.63***	−0.29	1.1	1.22	0.08	0.28	−1.71**	−2.14**	−1.45*	−0.63	−0.27	−1.17	0.62	−0.64	1.47*	0.35
Houston																	
	WTI	0.67	−0.93	0.22	0.77	−0.87	−0.21	−0.97	−1.17	−0.46	−0.92	0.01	0.23	0.28	0.57	1.84**	1.27
	ULSD	0.71	−0.56	1.14	0.69	−0.56	−1.54*	−0.13	−1.50*	1.52*	−0.84	1.54*	−0.41	−0.66	−0.38	0.91	0.68
	RBOB	0.8	−0.05	1.41*	1.64**	0.18	0.12	−1.39*	0.32	−1.08	−0.73	0.24	0.08	1.73**	−0.46	1.42*	−0.3
	BRENT	1.38*	−0.8	1.49*	0.88	0.61	0.15	0.02	−1.09	−0.48	−1.21	0.3	0.77	0.42	1.37*	1.70**	1.40*
	GASOIL	−1.03	−1.18	1.06	1.67**	−0.64	−1.26	−0.7	−0.83	−1.03	−1.14	0.66	1.93**	−0.21	0.19	−0.37	1.27
		Daily Data															
		IFO								MGO							
		2013	2014	2015	2016	2017	2018	2019	2020	2013	2014	2015	2016	2017	2018	2019	2020
Rotterdam																	
	WTI	0.57	1.48*	−1.05	1.79**	1.53*	1.25	−0.1	−2.13**	0.69	3.09***	−0.53	1.68**	1.98**	−0.05	−0.91	1.23
	ULSD	1.52*	−0.11	−1.09	2.39***	1.87**	−0.9	0.87	−0.88	1.52*	−1.45*	0.18	2.11**	2.58***	−0.72	0.53	−0.52
	RBOB	−1.06	−1.57*	−0.06	1.16	−1.08	−1.24	0.12	0.91	−0.42	−0.81	0.34	1.17	−1.01	−0.86	−0.71	1.08
	BRENT	0.73	1.18	−1.24	1.23	0.83	0.41	−0.42	−1.66**	−0.23	1.27*	0.03	0.82	1.47*	−1.25	−1.2	0.21
	GASOIL	−0.86	−0.09	−2.16**	0.53	−0.88	−0.66	0.59	−0.1	−0.31	0.64	−0.47	1.39*	−0.41	−0.95	−0.81	0.16
Singapore																	
	WTI	1.44*	0.16	−0.04	0.64	1.60*	0.48	−0.41	0.86	0.08	0.62	0.01	1.77**	2.34***	−0.49	−1.02	0.73
	ULSD	2.00**	−0.42	0.14	2.13**	−0.17	−0.69	−1.06	1.51*	0.94	−0.46	−0.81	0.58	2.61***	−1.08	−0.17	0.28
	RBOB	−1.08	−0.57	−0.87	1.52*	−1.41*	−1.92**	−1.11	1.07	−0.92	−0.57	−0.92	0.9	−1.07	0.47	−1.06	1.16
	BRENT	1.38*	1.31*	−0.72	0.32	0.83	−0.69	−0.81	1.78**	0.12	0.89	−0.97	0.62	1.08	−0.53	−0.93	1.36*
	GASOIL	−0.75	0.08	−1.93**	−0.29	−1.16	−0.5	−0.87	0.09	−0.17	−0.43	0.04	0.18	−1.18	−1.50*	−0.43	−0.34
Fujairah																	
	WTI	−1.18	2.00**	−0.54	1.11	−0.33	1.33*	−1.41*	−1.28*	−1.60*	−1.18	−1.53*	−0.77	0.31	−0.87	0.16	−0.34
	ULSD	2.90***	−0.34	0.69	1.04	0.73	−1.78**	−0.62	−1.07	1.38*	−0.93	−1.96**	−0.89	0.28	−1.67**	1.29*	0.52
	RBOB	−0.16	−1.12	−0.41	0.19	−1.03	−1.54*	−1.21	−0.84	−0.6	−1.34*	−1.37*	1.86**	−0.88	−1.03	0.14	−0.58
	BRENT	1.90**	0.95	−0.39	0.43	1.09	0.59	−1.66**	−1.17	0.12	0.26	1.81**	−0.03	−0.07	1.92**	−0.48	−0.47
	GASOIL	0.6	−0.27	−1.2	0.08	0.1	0.35	−2.04**	0.63	0.9	1.28*	0.33	−1.23	−0.39	1.65**	0.34	−0.08
Houston																	
	WTI	−0.39	1.37*	−0.66	−1.25	0.4	−1.1	−0.68	−0.53	−1.26	2.39***	−0.73	−1.2	0.93	−1.74**	−0.61	−1.1
	ULSD	1.05	−1.95**	−0.12	0.63	−0.88	0.96	−1.33*	−0.73	−0.16	−2.32***	−1.22	−0.64	−0.77	0.48	0.67	0
	RBOB	1.06	−1.48*	0.51	1.70**	−1.09	−1.01	−0.95	1.40*	−0.11	−1.97**	−1.33*	0.52	−1.07	−0.52	−1.44*	1.53*
	BRENT	0.03	−1.02	−0.84	−0.23	0.25	−0.01	−0.63	−1.76**	0.41	0.17	−0.43	−0.7	0.12	−2.31***	−0.54	−0.88
	GASOIL	−0.81	1.34*	−1.65**	−1.15	0.31	−0.05	−0.1	0.27	0.1	0.27	−0.3	−1.23	0.13	−1.47*	0.61	1.21

Note: Table reports the comparison of the DCC(benchmark) and ADCC GARCH models for given years. For each spot-futures pair, we report the Diebold–Mariano test statistics — the significantly more/less accurate forecasts with respect to the benchmark model are in bold/italics; significance at the 1%, 5%, and 10% levels are denoted by ***, **, and *, respectively.

models indicates very similar patterns (Figs. 1, 2). Moreover, we document high unconditional correlations between the optimal hedge ratios obtained from symmetric and asymmetric MGARCHs - the average unconditional correlation[14] across the ports and futures is 0.923/0.854 for IFO/MGO in the weekly hedging horizon and 0.960/0.904 in the case of the daily horizon. Our results thus support findings documented in Basher and Sadorsky (2016) where correlations of optimal hedge ratios from DCC and ADCC GARCHs were more than 0.95. Besides studying the optimal hedge ratios, we have also compared the pair-wise forecasting accuracy for individual years of our out-of-sample period. The overall results reported in Table 7 indicate similar performance of both DCC and ADCC models. Moreover, the results are qualitatively very similar to those presented in our main analysis (Tables 2 and 4). The similar performance of the symmetric and the asymmetric MGARCHs differ from results found in the papers of Radchenko (2005), Efimova and Serletis (2014) and Baruník et al. (2015) where asymmetries in oil markets were documented. Following Pan et al. (2014), we suggest that more sophisticated models might not generate better hedging outcomes due to larger estimation errors as a consequence of more parameters in the multivariate models. In addition,

[14] Detailed results are presented in Table 6.

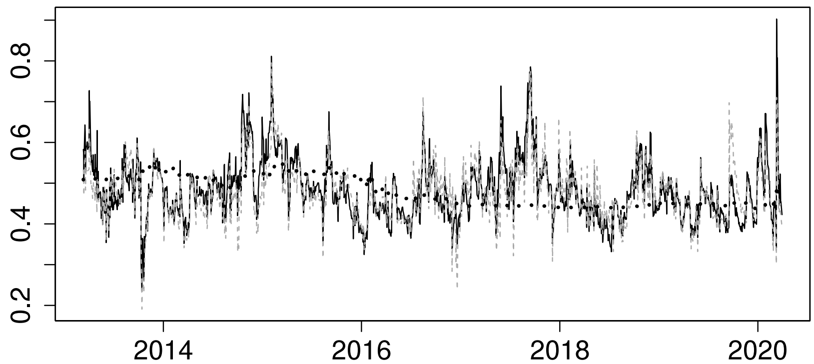

Fig. 2. Daily Rotterdam MGO - GASOIL optimal hedge ratios. Note: The OHRs from DCC are plotted with the solid black line, those from ADCC are the dashed dark gray line and those from OLS are the black dotted line.

dynamic hedge ratios are likely far too volatile to ascertain the highest hedging effectiveness across the whole range of commodities within the marine and shipping industries. If we combine these two premises and couple them with a market that is far too variable, we arrive at the conclusion that the simple OLS approach should be used as a benchmark for more complex models.

We conclude that it is convenient to assume that bunker prices are affected by the pricing of petroleum futures contracts, although they do not fully reflect the changes occurring in the derivatives market. Furthermore, we argue that there is more space to hedge low sulfur bunker fuels and that our setup is sufficiently robust given that four different locations were analyzed. Overall, the solution to the IMO 2020 cannot be obtained explicitly; however, we are optimistic that the commodities could be hedged in some interesting combinations to take advantage of the diversification effects, as aforesaid.

4. Conclusions

Our paper extends the earlier empirical literature on the bunker industry and connects it with the environmental regulations set by the International Maritime Organization. By considering four major bunkering hubs and the five most actively globally traded energy commodity futures, we study cross-hedging opportunities. We account for the intensity among crude oil, its refined products and two classes of bunker fuel oils.

Our empirical analysis reveals that the uncertainty regarding the price of bunker fuels can be reduced almost by 72%. Specifically, the hedging performance of the OLS and (A)DCC-GARCH methods, quantified by portfolio variance reduction, results in a hedging effectiveness index ranging from 4.27% to 71.94% when we rely on the weekly frequency and −0.61% to 21.88% in daily data analysis. The positive values of the hedging effectiveness index indicate potential economic gains by means of reduced bunker fuel price uncertainty. From the practical point of view, the lower fuel price uncertainty can directly translate into stabilized cash flows for the shipping companies and result in reduction of fuel price risk premium. Non-increasing (or even decreasing) risk premium can subsequently have a positive impact on the overall consumption of the globally traded goods. Since the consumption is an inherent part of the gross domestic product and the vast majority of goods are transported by marine vessels, our results are of great concern for economic agents worldwide.

Local conditions across megahubs undoubtedly affect the degree of hedging effectiveness, but the choice of derivatives is fairly universal. We have identified Gasoil and Brent to be the best hedging instruments around the globe. The out-of-sample performance also shows that low sulfur oils are more appealing spot contracts for Rotterdam and Singapore, while high sulfur oils are more attractive for Fujairah, and there is no clear preference for Houston. By utilizing rolling window analysis, we demonstrate that dynamic hedge models cannot consistently outperform their OLS equivalent. The hedging effectiveness is very similar across the symmetric and asymmetric MGARCH models, with only occasional superiority of the asymmetric version. We have not identified many desired effects for the naïve hedge — in the weekly data analysis, for certain spot-futures pairs, there is a positive variance reduction; however, competitors have statistically better performance. In the daily data analysis, the one-to-one hedging strategy increases the portfolio variance; hence, remaining unhedged is a better option in such a case. Overall, we are positive that active hedging can significantly reduce marine fuel prices' uncertainty.

CRediT authorship contribution statement

František Čech: Conceptualization, Software, Validation, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Data curation, Visualization. **Michal Zítek:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft.

Appendix A

See Tables 5–7

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106204.

References

Adams, Z., Gerner, M., 2012. Cross hedging jet-fuel price exposure. Energy Econ. 34 (5), 1301–1309.
Adland, R., Ameln, H., Bornes, E.A., 2020. Hedging ship price risk using freight derivatives in the drybulk market. J. Shipp. Trade 5 (1).
Alizadeh, A.H., Kavussanos, M.G., Menachof, D.A., 2004. Hedging against bunker price fluctuations using petroleum futures contracts: Constant versus time-varying hedge ratios. Appl. Econ. 36 (12), 1337–1353.
Baillie, R.T., Myers, R.J., 1991. Bivariate GARCH estimation of the optimal commodity futures hedge. J. Appl. Econometrics 6 (2), 109–124.
Baruník, J., Kočenda, E., Vácha, L., 2015. Volatility spillovers across petroleum markets. Energy J. 36 (3), 309–329.
Basher, S.A., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. Energy Econ. 54, 235–247.
Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econometrics 31 (3), 307–327.
Cao, Z., Harris, R.D., Shen, J., 2010. Hedging and value at risk: A semi-parametric approach. J. Futures Mark.: Futures Options Other Deriv. Prod. 30 (8), 780–794.
Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. J. Financ. Econom. 4 (4), 537–572.
Cecchetti, S.G., Cumby, R.E., Figlewski, S., 1988. Estimation of the optimal futures hedge. Rev. Econ. Stat. 623–630.
Chang, C.-L., McAleer, M., Tansuchat, R., 2011. Crude oil hedging strategies using dynamic multivariate GARCH. Energy Econ. 33 (5), 912–923.

Chen, S.-S., Lee, C.-F., Shrestha, K., 2004. An empirical analysis of the relationship between the hedge ratio and hedging horizon: A simultaneous estimation of the short-and long-run hedge ratios. J. Futures Mark.: Futures Options Other Deriv. Prod. 24 (4), 359–386.

Chu-Van, T., Ramirez, J., Rainey, T., Ristovski, Z., Brown, R.J., 2019. Global impacts of recent IMO regulations on marine fuel oil refining processes and ship emissions. Transp. Res. D 70, 123–134.

Cifarelli, G., Paladino, G., 2015. A dynamic model of hedging and speculation in the commodity futures markets. J. Financial Mark. 25, 1–15.

Dewally, M., Marriott, L., 2008. Effective basemetal hedging: The optimal hedge ratio and hedging horizon. J. Risk Financ. Manage. 1 (1), 41–76.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. J. Bus. Econom. Statist. 13 (3), 253–263.

Ederington, L.H., 1979. The hedging performance of the new futures markets. J. Finance 34 (1), 157–170.

Efimova, O., Serletis, A., 2014. Energy markets volatility modelling using GARCH. Energy Econ. 43 (5), 264–273.

Engle, R.F., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. 20 (3), 339–350.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. J. Finance 48 (5), 1779–1801.

Halff, A., Younes, L., Boersma, T., 2019. The likely implications of the new IMO standards on the shipping industry. Energy Policy 126, 277–286.

Hull, J.C., 2014. Fundamentals of Futures and Options Markets: Global Edition, first ed. Pearson.

Hung, J.-C., Chiu, C.-L., Lee, M.-C., 2006. Hedging with zero-value at risk hedge ratio. Appl. Financial Econ. 16 (3), 259–269.

IGU, 2017. Enabling Clean Marine Transport. Technical Report 4, International Gas Union, Barcelona.

Ji, Q., Fan, Y., 2011. A dynamic hedging approach for refineries in multiproduct oil markets. Energy 36 (2), 881–887.

Johnson, L.L., 1960. The theory of hedging and speculation in commodity futures. Rev. Econom. Stud. 27, 139–151.

Kolb, R.W., Okunev, J., 1992. An empirical evaluation of the extended mean-Gini coefficient for futures hedging. J. Futures Mark. 43 (1), 177–186.

Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financ. Quant. Anal. 28 (4), 535–551.

Ku, Y.-H.H., Chen, H.-C., Chen, K.-H., 2007. On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. Appl. Econ. Lett. 14 (7), 503–509.

Lien, D., 2009. A note on the hedging effectiveness of GARCH models. Int. Rev. Econ. Finance 18 (1), 110–112.

Lien, D., Shrestha, K., 2007. An empirical analysis of the relationship between hedge ratio and hedging horizon using wavelet analysis. J. Futures Markets: Futures Options Other Deriv. Prod. 27 (2), 127–150.

Lien, D., Tse, Y.K., 2000. Hedging downside risk with futures contracts. Appl. Financial Econ. 10 (2), 163–170.

Lien, D., Tse, Y.K., Tsui, A.K.C., 2002. Evaluating the hedging performance of the constant-correlation GARCH model. Appl. Financial Econ. 12 (11), 791–798.

Lien, D., Yang, L., 2008. Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. J. Bank. Financ. 32 (2), 187–198.

Lim, S.H., Turner, P.A., 2016. Airline fuel hedging: Do hedge horizon and contract maturity matter? J. Transp. Res. Forum 55 (1), 29–49.

Maghyereh, A.I., Awartani, B., Tziogkidis, P., 2017. Volatility spillovers and cross-hedging between gold, oil and equities: Evidence from the Gulf Cooperation Council countries. Energy Econ. 68, 440–453.

Menachov, D.A., Dicer, G.N., 2001. Risk management methods for the liner shipping industry: The case of the Bunker Adjustment Factor. Marit. Policy Manage. 28 (2), 141–155.

Merrick, J.J., 1988. Hedging with mispriced futures. J. Financ. Quant. Anal. 23 (4), 451–464.

Myers, R.J., 1991. Estimating time-varying optimal hedge ratios on futures markets. J. Futures Mark. 11 (1), 39–53.

Myers, R.J., Thompson, R.S., 1989. Generalized optimal hedge ratio estimation. Am. J. Agric. Econ. 71 (4), 858–867.

Pan, Z., Wang, Y., Yang, L., 2014. Hedging crude oil using refined product: A regime switching asymmetric DCC approach. Energy Econ. 46 (C), 472–484.

Panasiuk, I., Turkina, L., 2015. The evaluation of investments efficiency of SO_X scrubber installation. Transp. Res. D 40, 87–96.

Radchenko, S., 2005. Oil price volatility and the asymmetric response of gasoline prices to oil price increases and decreases. Energy Econ. 27 (5), 708–730.

Samitas, A., Tsakalos, I., 2010. Hedging effectiveness in shipping industry during financial crises. Int. J. Financ. Mark. Deriv. 1 (2), 196–212.

Ship & Bunker, 2020. Global 4 ports average. https://shipandbunker.com/prices/av/global/av-g04-global-4-ports-average.

Stefanakos, C.N., Schinas, O., 2014. Forecasting bunker prices; a nonstationary, multivariate methodology. Transp. Res. C 38 (1), 177–194.

UNCTAD, 2017. Review of Maritime Transport, 2017.

Wang, X., Teo, C.-C., 2013. Integrated hedging and network planning for container shipping's bunker fuel management. Marit. Econ. Logist. 15 (2), 172–196.

Wang, Y., Wu, C., 2012. Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models? Energy Econ. 34 (6), 2167–2181.

Wang, Y., Wu, C., Yang, L., 2015. Hedging with futures: Does anything beat the naïve hedging strategy? Manage. Sci. 61 (12), 2870–2889.

Zhu, M., Li, K.X., Lin, K.-C., Shi, W., Yang, J., 2020. How can shipowners comply with the 2020 global sulphur limit economically? Transp. Res. D 79, 931–955.