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How Does Oil Future Price Imply Bunker Price—Cointegration and Prediction Analysis

Yanhui Chen *, Jinrong Lu and Mengmeng Ma

Department of International Trade and Finance, Shanghai Maritime University, Shanghai 201308, China; 201930710001@stu.shmtu.edu.cn (J.L.); 202130710011@stu.shmtu.edu.cn (M.M.)
* Correspondence: chenyh@shmtu.edu.cn

Abstract: This paper investigates how oil's future price implies the bunker price through cointegration analysis first. A cointegration test confirms the long-run equilibrium condition of bunker and oil future prices. Based on the cointegration relationship, we construct VECM model to forecast bunker prices. In addition, we also consider ARMA, ARMAX, and VAR models for certifying whether considering the long-run equilibrium between bunker and oil future prices is helpful in prediction. One-step-ahead and four-step-ahead forecasting are considered and two out-of-sample datasets are used. The empirical results show that the increase in the value of the error correction term in the VECM model has the effect of pulling down the bunker return. VECM performs better than other models in prediction. The Crude Oil Future Contract 1 has better forecasting performance for bunker prices with VECM in the 1-step-ahead forecast, while Crude Oil Future Contract 3 performs slightly better than Crude Oil Future Contract 1 in the 4-step-ahead forecast.

Keywords: cointegration analysis; oil future price; bunker price; forecasting

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1. Introduction

Marine transportation is an integral part of transportation networks, and one of the most important ways for international trade. With the acceleration of the economic globalization process, international trade is more and more frequent. With its natural navigation channel, large carrying capacities, and relatively low freight charges, marine transportation is active and accounts for more than 80% of the total volume of international freight [1]. Other than the large investment in infrastructure construction, a bunker is a significant operating cost for shipping companies, accounting for about 30–70% of the operating cost based on different bunker prices [2,3] . Bunker is mainly the heavy residual product left after gasoline, kerosene, and diesel oil from crude oil refining, as a result, its price is closely linked to the crude oil price. However, it is also affected by the relationship between supply and demand, showing volatility related to but inconsistent with the crude oil price. In the first quarter of 2021, WTI and Brent crude oil spot prices increased by 24.95% and 23.00%, respectively, because of world economic recovery and US inflation. During this period, the MGO (Marine Gas Oil) prices of Fujairah, Rotterdam, and Singapore increased by 26.31%, 20.72%, and 20.03%, respectively, and the VLSFO (Very Low Sulphur Fuel Oil) of these three ports increased by 19.38%, 17.41%, and 16.28%, respectively. Due to the uncertainty of bunker prices, shipping companies are exposed to the risk of bunker price changes. The analysis and forecasting of bunker prices are of great importance so that shipping companies can control the risk of bunker price fluctuations and control their operating costs.

Although previous studies have realized the importance of bunker, they mainly focus on controlling bunker fuel cost and reducing the purchase cost by optimizing refueling strategy. As for crude oil futures prices, most of the existing literature has studied the cointegration relationship between crude oil future prices and spot prices, or the relationship between crude oil future market and other commodity markets. At present, there is no literature on the relationship between the bunker price and the crude oil future price, which is also the novelty and originality of this paper.

This paper aims to analyze the relationship between bunker and crude oil future prices quantitatively. Firstly, this paper confirms the cointegration relationship between bunker and oil future prices. As a result, the VECM becomes reasonable to capture the long-term equilibrium relationship of bunker and oil future prices. ARMA, ARMAX, and VAR are also considered in predicting bunker prices which can test whether the cointegration relationship is effective in prediction. One-step-ahead and four-step-ahead forecasts are considered because these two prices are the most concerning issue in the industry. Moreover, two crude oil futures contracts are involved in the analysis because we want to check which contract implies future bunker prices more reliably and suitably. The results show that the VECM model performs better than the other three models, which means oil futures prices imply bunker prices through the long-term equilibrium cointegration relationship. The results also show crude oil future contract 1 is more reliable in the one-step-ahead prediction. Oil future contract 3 is just a little better in four-step-ahead prediction. As a result, in four-step-ahead prediction, the prediction results based on two future contracts should be considered. The results of this paper are conducive to the liner companies to have sufficient time to adjust the transportation refueling plan and use crude oil futures for hedging to avoid economic losses in time. Moreover, forward trading regarding bunker oil has gained the attention of some large financial firms, such as Goldman Sachs, in recent years. Though accurate forecasting of bunker oil prices is of great importance and helps shipping companies make timely adjustments to their operating strategies.

The structure of this paper is as follows. Section 2 reviews the literature. Section 3 presents the data and the cointegration analysis. Section 4 focuses on the prediction analysis. Section 5 conducts the impulse response analysis and makes a supplementary. Finally, Section 6 concludes this study.

2. Literature Review

Bunker price is crucial for ship operators, Abouarghoub and Haider [1] mention that the cost of the bunker is the key cost for ship operators, and the change in bunker price will have a great impact on the operation capacity. Notteboom and Vernimmen [2] study the impact of bunker oil price changes on the cost of liner service operations. The rise in bunker oil prices correspondingly increases the transportation costs of shipping companies. The purpose of profit-making companies is to maximize corporate profits. As a result, price analysis of bunkers used in ship transportation cargo is of great importance. However, most of the existing studies focus on controlling fuel oil costs through bunker management strategy. For example, Yao et al. [4] investigated a bunker fuel management strategy for a single shipping liner service and studied the relationship between sailing speed and fuel consumption rate. They use an empirical model to explain the relationship between bunker oil consumption rate and sailing speed for container ships of different sizes, which is conducive to reducing shipping costs and improving service quality and efficiency for shipping companies. Wang, Gao et al. [5] use a mixed-integer nonlinear programming model which simultaneously considers sailing speeds, bunkering ports, bunkering volume, and loading amounts to maximize cargo revenue and minus bunker cost. Ghosh, Lee et al. [6] focus on the cost optimization strategy with bunkering contracts, and formulate a dynamic programming model to minimize the total bunkering cost. There are also many studies in the extant literature on the optimal bunker refueling strategies for liner shipping, in which ways the operators can control the cost of bunker oil. Plum, Pisinger et al. [7] mention that fluctuations in bunker prices are usually related to crude oil prices, but prices vary significantly between ports, so the bunker purchasing cost optimization problem needs to be reformulated daily, but bunker purchasing is generally made by contract a few weeks prior to arrival the port, which complicates the adjustment of the optimal plan. De, Choudhary et al. [8] consider stochastic fuel consumption for different segments, stochastic bunker prices for each port, and different fuel refueling strategies to determine the optimal fuel management strategy. These researches show that bunker oil price is closely related to the operation of shipping companies and occupies an important position. Because the general trend of bunker prices is fluctuating and uncertain, even on the same day, bunker oil prices may vary significantly from port to port [6].

Although the bunker price is important, the direct analysis of the bunker price is few. Stefanakos and Schinas [9] argue that the efficient forecasting of bunker prices is of ship operators' interest, and there is also a direct relationship between bunker prices and financial results, and that incorrect forecasting of bunker prices leads to incorrect estimates of bunker price fluctuations, resulting in incorrect hedging ratios and risk management strategies, which means catastrophe for the normal operation of liner service operations. They used Vector Auto-Regressive Moving Average (VAR-MA) model to forecast a tetra-variate and an octa-variate time series of bunker prices, the predicted results are in good agreement with the actual values. Due to the importance of bunker price prediction, they also use fuzzy time series forecasting techniques to predict bunker prices [10].

In a short summary, most of the existing literature focuses on the optimal bunker refueling strategy and bunker management. Bunker price prediction is an interest of the researchers; however, these researchers just considered the bunker market. There is limited literature to study the bunker price considering another energy market.

For crude oil futures, it has two indispensable functions; one is to hedge and reduce the potential risk for investors, the other is the function of price discovery. The oil futures prices reflect the price that both the buyer and the seller agree on. Thus, crude oil futures prices contain direct information about investors' expectations of future prices for the crude oil commodity [11]. Most of the existing literature investigates the relationship between crude oil future prices and spot oil prices or other commodity markets. Silvério and Szklo [12] through the empirical analysis of WTI spot and WTI futures, find that for WTI, the contribution of the future market in price discovery is increasing. Zhang and Wang [13] find that there is a long-term equilibrium relationship between futures and spot prices of crude oil, but the futures market is more mature and has better market efficiency and price discovery functions. Jiang, Marsh [14] use a vector error correction model to study the price transmission between the U.S. crude oil, corn, and plastic markets and find that the crude oil price is a factor that causes the changes in the plastic and corn futures markets. In addition, there is also a correlation between the crude oil and corn futures markets. Alizadeh and Nomikos [15] investigate the dynamic relationship between oil future prices and tanker freight rates. Chu, Hoff et al. [16] indicate that in the prediction of oil spot price, futures-based forecasts perform better than the no-change forecast across long-term horizons (one to five years). Bai and Kavussanos [17] examine how to use the petroleum future contracts to manage the risk results from the bunker spot price fluctuations. Other related literature includes Chang and Lee [18], Lee and Zeng [19], Chen, Lee et al. [20], Gulley and Tilton [21], and Liu Wang et al. [22]. The existing literature on the relationship between crude oil future prices and spot prices has been very sufficient. However, at present, there is limited literature on the relationship between crude oil futures and bunker oil. Bunker is a product of crude oil split distillation, so its price should be closely related to the oil price. As oil future price contains the information of future spot oil price; it is reasonable to investigate how oil future prices imply bunker prices. In this way, shipping enterprises can make timely adjustments and decisions. As crude oil future is the most active futures contract in the world shipping enterprises and can consider using the crude oil future to manage risk when the bunker prices change, thus controlling their operation costs and maximizing profits. For this reason, this research fills this gap by investigating the relationship between bunker prices and oil future prices.

Cointegration analysis is very popular in analyzing the co-movement of two non-stationary time series. For example, Aftab, Ahmed et al. [23] investigate the nexus between carbon emissions, energy consumption and economic progress for Pakistan by cointegration and autoregressive distribution lag methods. Zakaria, Khiam et al. [24] analyze the impact of world oil prices on inflation in South Asian countries, using Cointegration, VAR, and nonlinear analysis. After the cointegration relationship is confirmed, the vector error correction model (VECM) is usually applied to the model time series. For example, Alizadeh and Nomikos [15] check the causal relationship between WTI futures and shipping freight costs using the Vector Error Correction model. Besides ARDL, Aftab, Ahmed et al. [23] also apply the VECM to determine feedback effect in a bivariate model. Impulse response analysis is often used with VECM too because it can provide the support of causality status between the variables in the VECM system [25]. For example, Danish Wang et al. [26] use the impulse response function to reveal that CO_2 emission rises due to forecast error stemming from energy crises. Mensah, Triacca et al. [27] also conduct impulse response analysis with VECM. So this paper adopts their research methods to explore how crude oil future prices imply bunker prices.

3. Data Description and Cointegration Analysis

3.1. Data Description

The paper includes bunker fuel (MGO, Marine Gas Oil) weekly price data from three ports, namely, Rotterdam, Singapore, and Fujairah, as well as two crude oil future contracts (contract 1 and 3) from NYEX (The New York Mercantile Exchange). Approximately 831 data points are selected for analysis for the period 30 December 2005 to 26 November 2021. Taking the data from 30 December 2005 to 22 February 2019 as the in-sample, that is 687 observations in total. We use data from 1 March 2019 to 26 November 2021 as the out-of-sample(144 weekly price data) to investigate the predictive performance of different models. Bunker price data are downloaded from Shipping Intelligence Network provided by Clarkson Research Services Ltd. in London, UK. Crude oil future price is downloaded from U.S. Energy Information Administration.

In this paper, the MGO prices of Fujairah, Rotterdam, and Singapore and the two crude oil future contract prices are treated logarithmically, and their price trends are shown in Figure 1. From the figure, it can be seen that the bunker price fluctuates greatly. The fluctuation trend of the bunker oil prices in all three ports is almost the same as that of the two crude oil future contracts. Both bunker and crude oil future prices have risen since the second half of 2020. According to Table 1, the average, minimum and maximum bunker prices in Fujairah are higher, and the standard deviation is lower than those in Rotterdam and Singapore. However, all three ports have big standard deviation value, which indicates great price volatility. The skewness values for bunker prices of the three ports and crude oil future prices are all greater than zero, indicating right-skewed distributions. The kurtosis indicators are less than 3, indicating a fat-tailed distribution. The five columns on the right side of Table 1 are the logarithm changes of MGO prices and crude oil future prices. In terms of logarithm changes, MGO, and crude oil futures are not significantly different. Referring to the skewness and kurtosis indicators, the logarithm changes of the bunker and crude oil future prices exhibit left-skewed distributions. Crude oil future contract 1 has a higher kurtosis coefficient than other series, making its kurtosis finer.

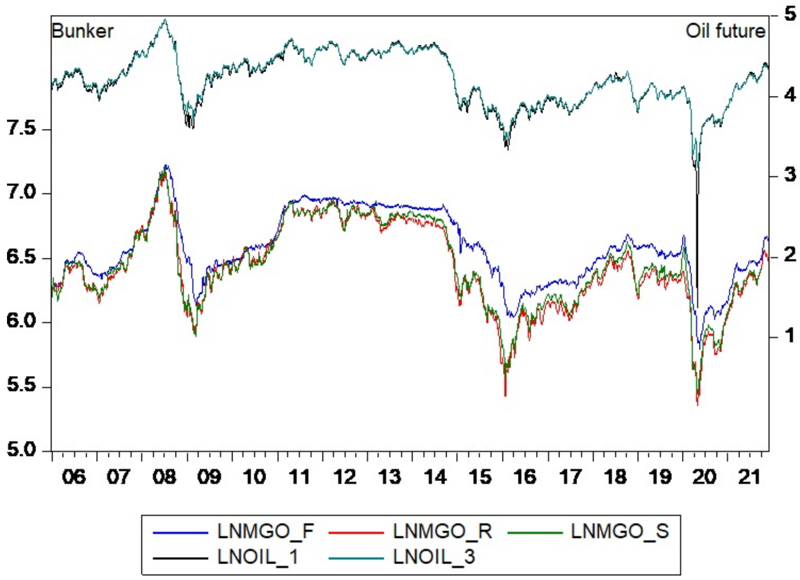

Figure 1. The trend of MGO and oil future prices (Data source: Shipping Intelligence Network and U.S. Energy Information Administration).

Table 1. Some key summary statistics (30 December 2005–24 September 2021).

	MGO_R	MGO_S	MGO_F	Oil_1	Oil_3	ΔMGO_R	ΔMGO_S	ΔMGO_F	ΔOil_1	ΔOil_3
Mean	650.08	662.49	746.26	70.661	71.478	0.0003	0.0003	0.0003	0.0002	0.0002
Maximum	1317.5	1360.0	1375.5	142.46	143.39	0.1987	0.1964	0.1269	1.3914	0.1844
Minimum	211.50	232.00	329.25	3.9200	22.670	−0.2851	−0.2621	−0.1949	−1.6351	−0.3241
Std. Dev.	213.45	212.22	206.71	22.675	22.005	0.0450	0.0404	0.0269	0.0879	0.0413
Skewness	0.4728	0.4930	0.5219	0.3306	0.3873	−0.3637	−0.5224	−1.1853	−3.0312	−1.1757
Kurtosis	2.4675	2.5252	2.4855	2.5410	2.5192	7.1749	8.7501	11.451	223.93	11.786

Note: (1) Oil_1 and Oil_3 indicate Crude Oil Future Contract 1 and 3 respectively. (2) Δ indicates the logarithm change. (3) The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

The Jarque–Bera test (JB test in Table 2) aims to test whether the series is normally distributed. The null hypothesis is the data that shows the normal distribution. As all the JB test statistic values are large, we reject the hypothesis at the 1% significance level.

Table 2. The Stationary test and JB test.

	$LnMGO_R$	$LnMGO_S$	$LnMGO_F$	$LnOil_1$	$LnOil_3$
JB test	10.576 ***	9.2268 ***	14.549 ***	956.92 ***	14.353 ***
ADF test	−1.9750	−2.2646	−2.1899	−2.7922 *	−2.4010
KPSS test	0.9759 ***	0.8618 ***	0.7336 **	1.1098 ***	1.2602 ***
	ΔMGO_R	ΔMGO_S	ΔMGO_F	ΔOil_1	ΔOil_3
JB test	614.35 ***	1168.4 ***	2635.4 ***	1671000 ***	2829.5 ***
ADF test	−27.347 ***	−16.857 ***	−12.121 ***	−24.470 ***	−22.209 ***
KPSS test	0.0597	0.0553	0.0762	0.0341	0.0486

Note: (1) Refer to the stationary test; intercept is included in the test equation for all the series. (2) The null hypothesis of the ADF test is that the series has a unit root. The lag length for the ADF test is 20. The test critical values of ADF test (Adj. *t*-Stat.) are −3.4380, −2.8648, −2.5686 at 1%, 5%, and 10% levels, respectively. (3) The null hypothesis of the KPSS test is that the series is stationary. The asymptotic critical values of KPSS test (LM Stat.) are 0.7390, 0.4630, 0.3470 at 1%, 5%, and 10% levels, respectively. (4) ***, **, * denote the significance at 1%, 5% and 10%, respectively.

Both the Augmented Dickey–Fuller (ADF) test and KPSS test are used to test the stationarity and the results are shown in Table 2. As with the ADF test, we fail to reject the null hypothesis of a unit root in the logarithmic bunker and oil future contract 3 price series at conventional significance levels. After differencing the series, the ADF test results are significant, indicating that the logarithmic bunker and crude oil future price series are stationary in their first-order differences. Different from the ADF test, the KPSS test has a null hypothesis of no unit root. From Table 2, we reject the null hypothesis of no unit root in the logarithmic bunker and oil future price series, but their first-order differences are stationary according to the KPSS test results.

3.2. Cointegration Analysis

Figure 1 illustrates the similar trends of MGO and oil future prices. Moreover, the logarithmic MGO and oil future prices are not stationary, but they have the same order of integration. Engle and Granger [28] pointed out that even though two series are non-stationary, a linear combination of them may be stationary. As a result, the test for the cointegration among the variables is necessary to see if the logarithmic MGO and oil future prices share a common trend, including long term relationship.

In this section, the Johansen cointegration test was performed for the MGO and the crude oil future prices. It makes use of two likelihood ratio (LR) statistics: the trace statistic (λ_{trace}) and the maximum eigenvalue statistic (λ_{max}) [29].

$$\lambda_{trace} = -T \sum_{i=r+1}^{K} \log(1 - \hat{\lambda}_i) \tag{1}$$

$$\lambda_{max} = -T \log(1 - \hat{\lambda}_{r+1}) \tag{2}$$

where $\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_K$ are $(K - r)$ smallest estimated eigenvalues. For more details on the application of Johansen test please refer to Mensah et al. [27]. The sequential test for the trace test relies on the hypothesis

Hypothesis 1. *H0: $r = r_0$ against H1: $r_0 < r < K$. (K is the number of the variables).*

The sequential test for the maximum eigenvalue relies on the hypothesis

Hypothesis 2. *H0: $r = r_0$ against H1: $r = r_0 + 1$.*

If the cointegration relationship is confirmed, it can be concluded that there is a long-run relationship between the variables. As shown in Table 3, in the cointegration test between the crude oil future contract 1 and the MGO prices of Rotterdam, Singapore, and Fujairah, both Trace and the Maximum eigenvalue statistics firmly reject the hypothesis of no cointegration at the 5% significance level. In the cointegration test between the crude oil future contract 3 and the MGO prices of Rotterdam, Singapore, and Fujairah, both Trace and the Maximum eigenvalue statistics firmly reject the hypothesis of no cointegration at the 5% significance level. Both crude oil future contract 1 and 3 has a cointegration relationship with the MGO price series of Rotterdam, Singapore, and Fujairah. The cointegrating parameters and optimal lag orders are shown in Table 3. Take the MGO price in Rotterdam and the oil future contract 1 price as an example, the error correction term is

$$LnMGO_{R,t-1} = 2.1231 + 1.0247 LnOil_{1,t-1} \tag{3}$$

Equation (3) shows a positive correlation between oil future contract 1 and MGO. It can be found that a 1 percent increase in oil future price leads to 1.0247 percent growth in the MGO. This also means that a permanent increase in the price of oil future contract 1 will propel MGO price growth.

Table 3. The Johansen cointegration test results.

	H0	TRACE	EIGENV	Bunker	Oil Future	Constant	LAG
	Oil future contract 1						
Rotterdam	r = 0 *	47.1838	43.4263				3
	r = 1	3.7575	3.7575				3
	Cointegrating parameters			1.0000	−1.0247	−2.1231	
Singapore	r = 0 *	42.6368	37.8457				3
	r = 1	4.7911	4.7911				3
	Cointegrating parameters			1.0000	−0.9981	−2.2581	
Fujairah	r = 0 *	59.6227	53.0320				3
	r = 1	6.5907	6.5907				3
	Cointegrating parameters			1.0000	−0.9407	−2.6314	
	Oil future contract 3						
Rotterdam	r = 0 *	28.0200	23.8535				1
	r = 1	4.1666	4.1666				1
	Cointegrating parameters			1.0000	−1.0978	−1.7934	
Singapore	r = 0 *	22.2509	17.4352				2
	r = 1	4.8158	4.8158				2
	Cointegrating parameters			1.0000	−1.0535	−2.0021	
Fujairah	r = 0 *	66.6750	58.7704				2
	r = 1	7.9045	7.9045				2
	Cointegrating parameters			1.0000	−0.9866	−2.4169	

Note: (1) The lag order is determined by BIC. (2) * denotes rejection of the hypothesis at the 0.05 level.

4. Prediction Analysis

4.1. Model Specification

It is found that the crude oil future prices and the MGO prices are cointegrated in the last section. By utilizing the cointegration relationship, the VECM model can be built to predict the price of MGO. In addition, we also considered the ARMA, ARMAX, and VAR models to explore the performance of these models in predicting the MGO prices.

4.1.1. ARMA and ARMAX

Autoregressive Moving Average (ARMA) is the most basic model in time series analysis and it is usually taken as the benchmark model in prediction performance evaluation. ARMAX is an extension of ARMA by including exogenous variables.

The ARMA model considers the effect of the series' own lagged term and random disturbance term on the current series value (Shown in Equation (4)). The ARMAX model adds exogenous variables to investigate the impacts of these exogenous variables. In this paper, the return series of crude oil future prices lagging by one period is taken as the exogenous variable in ARMAX, and the influence on the prediction effect of MGO price after adding the exogenous variable of the return of crude oil futures is considered (Shown in Equation (5)).

$$\Delta MGO_t = c + \sum_{i=1}^{p} \phi_i \Delta MGO_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

$$\Delta MGO_t = c + \sum_{i=1}^{p} \phi_i \Delta MGO_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \beta \Delta OilFuture_{t-1} + \varepsilon_t \tag{5}$$

4.1.2. VAR

VAR is constructed as a function of the lagged terms of each endogenous variable in the system. In this paper, the VAR model is constructed by taking the MGO returns and crude oil future returns as the endogenous variables in the system and using their lagged terms to construct a model to analyze and forecast MGO prices (Shown in Equation (6)).

$$\begin{aligned} \Delta MGO_t &= c_1 + \sum_{i=1}^{p} \varphi_{1,i} \Delta MGO_{t-i} + \sum_{i=1}^{p} \tau_{1,i} \Delta OilFuture_{t-i} + \varepsilon_{1,t} \\ \Delta OilFuture_t &= c_2 + \sum_{i=1}^{p} \varphi_{2,i} \Delta MGO_{t-i} + \sum_{i=1}^{p} \tau_{2,i} \Delta OilFuture_{t-i} + \varepsilon_{2,t} \end{aligned} \quad (6)$$

The best lag order of VAR is determined by Schwarz Criterion (SC), which is also known as Bayesian Information Criterion (BIC), because it also considers the number of the parameters in the models. The value of SC is calculated by the following equation:

$$SC = -2l/T + n \ln T/T \quad (7)$$

where n is the number of the estimated parameters and l is the log-likelihood value which is calculated by assuming that it obeys multivariate normal distribution. Table 4 shows the BIC values for lags 1–5. The values in bold indicate the optimal lags selected by the criteria.

Table 4. Lag selection using Bayesian information criteria.

Lag	ΔMGO_R ΔOil_1	ΔMGO_R ΔOil_3	ΔMGO_S ΔOil_1	ΔMGO_S ΔOil_3	ΔMGO_F ΔOil_1	ΔMGO_F ΔOil_3
1	−5.6822	**−7.9498**	−5.8112	−7.9563	−5.8112	−7.9563
2	−5.6866	−7.9295	−5.8455	**−7.9590**	−5.8455	**−7.9590**
3	**−5.7064**	−7.9131	**−5.8651**	−7.9451	**−5.8651**	−7.9451
4	−5.6793	−7.8882	−5.8465	−7.9288	−5.8465	−7.9288
5	−5.6831	−7.8798	−5.8525	−7.9137	−5.8525	−7.9137

Note: The bold numbers indicate the smallest BIC values for different bunker and future combinations.

4.1.3. VECM

The VECM is a model of VAR with cointegration constraints. Using the information presented in the previous section, one can construct a VECM model to analyze the dynamic relationship between MGO and crude oil futures yields. ecm_{t-1} in Equation (8) is the error correction term, which is established on the basis that bunker and crude oil future prices have a cointegration relationship. The error correction term indicates the long-run dynamics that although bunker and crude oil future prices are disequilibrium at any given time, but they have the tendency to adjust themselves towards equilibrium.The short-run dynamics is presented by $\sum_{i=1}^{p-1} \tau_{1,i} \Delta OilFuture_{t-i}$ in Equation (8). In the following equation, p is the optimal lag in the VAR model. So the lag order of VECM is $p-1$.

$$\begin{aligned} \Delta MGO_t &= c_1 + \alpha_1 ecm_{t-1} + \sum_{i=1}^{p-1} \varphi_{1,i} \Delta MGO_{t-i} + \sum_{i=1}^{p-1} \tau_{1,i} \Delta OilFuture_{t-i} + \varepsilon_{1,t} \\ \Delta OilFuture_t &= c_2 + \alpha_1 ecm_{t-1} + \sum_{i=1}^{p-1} \varphi_{2,i} \Delta MGO_{t-i} + \sum_{i=1}^{p-1} \tau_{2,i} \Delta OilFuture_{t-i} + \varepsilon_{2,t} \end{aligned} \quad (8)$$

4.2. Model Estimation Results

According to statistics, considering Singapore ranks first among the ten largest refueling ports in the world in 2020, it is more representative than the other two ports. This section discusses the estimation results based on the MGO prices in Singapore. The model parameter estimation results of the models used in this research are shown in Table 5.

Table 5. Estimated results (MGO in Singapore).

Parameters	Oil Future Contract 1		Oil Future Contract 3	
	Coefficient Estimate	*t*-Statistic	Coefficient Estimate	*t*-Statistic
		ARMA		
ϕ_1	0.8131 ***	10.3244		
θ_1	−0.6983 ***	−7.2539		
		ARMAX		
ϕ_1	0.6930 ***	5.1070	0.5550 ***	3.3644
ϕ_2	0.0778 *	1.7134	0.1796 ***	4.5020
θ_1	−0.6549 ***	−4.9528	−0.7110 ***	−4.2377
β	0.0644 ***	3.7401	0.3469 ***	7.8465
		VAR		
$\varphi_{1,1}$	0.0320	0.7892	−0.1990 ***	−3.8250
$\varphi_{1,2}$	0.0735 *	1.7853	0.0952 *	1.8504
$\varphi_{1,3}$	−0.0028	−0.0706	–	–
$\tau_{1,1}$	0.0838 ***	4.4933	0.4115 ***	8.2375
$\tau_{1,2}$	0.0141	0.7193	−0.0076	−0.1467
$\tau_{1,3}$	0.0784 ***	4.1674	–	–
		VECM		
α_1	−0.0301 **	−2.0298	−0.0444 ***	−2.9061
$\varphi_{1,1}$	0.0595	1.4481	−0.1825 ***	−3.5863
$\varphi_{1,2}$	0.1258 ***	3.1764	–	–
$\tau_{1,1}$	0.0489 **	2.3906	0.3969 ***	7.8463
$\tau_{1,2}$	−0.0234	−1.2077	–	–

Note: ***, **, * denote the significance at 1%, 5% and 10%, respectively.

In Table 5, the optimal lags of ARMA and ARMA are also determined by the BIC value. For crude oil future 1, almost all of the parameters estimation results of AR terms and MA terms in ARMA and ARMAX are significant at the 1% level. The parameter before the exogenous variable, crude oil future price return, is significant at 1%. The positive value indicates the bunker price increases with the oil crude future price. Additionally, the random disturbances term is negatively related to the current return rate. The VAR model considers the lagging terms of both the MGO return and the crude oil future return. The results indicate that the lagging terms of both returns have certain impacts on the MGO price return. For both datasets, the parameters' signs of the AR terms in the VECM are consistent with those of the VAR. For the MGO returns and oil future contract 1 returns, the parameter's sign of the MA(2) term in the VECM is not consistent with that of the VAR. But both of them are not significant. For both datasets, the parameters of the error correction terms are significant, which indicates the long-run equilibrium conditions significantly affect the short-run dynamics of bunker prices through an error correction mechanism. The parameters are negative, indicating that the increase in the error correction term's value has the effect of lowering the MGO returns, and the decrease in the error correction term's value has the effect of increasing the MGO price returns; in other words, the long-run equilibrium between MGO and oil future prices stabilizes the MGO price returns. Referring to the short-run dynamics between the MGO and oil future prices, the first lag of the oil future returns has a positive impact on the MGO price returns. The oil future contract 1 returns increase by 1% and, consequently, the MGO returns increase by 0.0489%. The oil future contract 3 returns increase by 1% and the MGO returns increase by 0.3969%. The second lag of the oil future contract 1 returns also impacts the MGO returns. However, this impact is weaker than the impact from the first lag.

4.3. Prediction Performance

Two prediction performance evaluation methods are used in this paper. Root mean square error (RMSE) is the most widely used method of evaluation. The better the forecast is, the smaller the mean square forecast error is. The closer to zero the value is, the better the forecasting performs. Another method is the Theil's inequality coefficient, also known as Theil's U. It provides a measure of how well the predicted value compares to the observed value, which helps to assess whether a good forecasting model is better than a naive prediction that repeats the previous observation, with the same evaluation criteria as RMSE. The calculation of RMSE and Theil's U is shown in Equations (9) and (10).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y_i})^2} \tag{9}$$

$$Theil'sU = \frac{\sqrt{\frac{1}{n}\sum_i (\hat{y}_i - y_i)^2}}{\sqrt{\frac{1}{n}\sum_i \hat{y}_i^2} + \sqrt{\frac{1}{n}\sum_i y_i^2}} \tag{10}$$

While the in-sample performance of the prediction model is not necessary to indicate the out-of-sample performance. Out-of-sample prediction can be used to measure the model's performance more subjectively. In this paper, the out-of-sample forecast period is from 1 March 2019 to 26 November 2021, which includes 144 observations. There are two types of forecast intervals, the one-step-ahead forecast and four-step-ahead forecast.

The results of RMSE and Theil's indicators in the one-step-ahead are shown in Table 6. When the ARMA, ARMAX, VAR, and VECM models are used to forecast the price of MGO, the effect of the MGO price predicted by the ARMA model is better than that of the ARMAX model, indicating that the prediction performance of the ARMA model will be reduced when considering the crude oil future returns. So only simply involving crude oil future returns is not effective in predicting MGO prices. In the out-of-sample forecast results of crude oil futures contract 1 and MGO price, the VECM model has the smallest root mean square error-index and Theil's U index. It appears that the VECM model demonstrates better forecasting performance than ARMA, ARMAX, and VAR models.

Referring to crude oil future contract 3 and MGO prices, when it comes to predicting MGO prices of Rotterdam and Fujairah, the VECM performs better than the other two models. In the prediction of MGO price of Singapore, the ARMAX model is the best and it performs slightly better than the VAR and VECM models. Compared with crude oil futures contract 1 and crude oil futures contract 3, crude oil futures contract 1 has better prediction performance using the VECM model, which indicates that the prediction ability of the model is improved after considering the cointegration relationship between the returns of MGO and crude oil future contract 1. As compared to Rotterdam, Singapore, and Fujairah, the RMSE and Theil's of the one-step-ahead forecast for Fujairah have the smallest weekly price relationship with crude oil futures, which indicates that the forecast effect on the MGO price of Fujairah port is good.

Table 6. 1-step-ahead Prediction Performance (1 March 2019–26 November 2021, 144 observations).

	Rotterdam		**Singapore**		**Fujairah**	
	RMSE	Theil's U	RMSE	Theil's U	RMSE	Theil's U
ARMA	5.4105	0.4380	4.9345	0.3967	3.3128	0.2597
	Oil future contract 1					
ARMAX	8.9108	0.7212	8.3100	0.6680	3.5014	0.2744
VAR	5.0130	0.4058	4.7971	0.3857	3.2027	0.2510
VECM	**4.9577**	**0.4013**	**4.7501**	**0.3819**	**3.0387**	**0.2382**
	Oil future contract 3					
ARMAX	5.6163	0.4546	5.1414	0.4133	3.2227	0.2526
VAR	5.6341	0.4561	5.1864	0.4169	3.1698	0.2484
VECM	5.5921	0.4527	5.1443	0.4136	3.1851	0.2497

Note: The bold numbers indicate the smallest RMSE or Theil's U in the prediction of different ports' bunker prices.

The results of the four-step-ahead prediction are shown in Table 7 . When the crude oil future contract 3 is used to make an out-of-sample prediction on MGO, the values of RMSE and Theil's U of the VECM model are lower than those of other models. This implies that the VECM model based on the cointegration between the MGO returns and the crude oil future returns can improve prediction accuracy. However, it doesn't mean crude oil future 3 with VECM is most suitable to conduct a four-step-ahead prediction, because crude oil future 1 with VECM achieves better RMSE and Theil's U values in predicting the MGO prices in Rotterdam.

Table 7. 4-step-ahead Prediction Performance (1 March 2019–26 November 2021, 144 observations).

	Rotterdam		**Singapore**		**Fujairah**	
	RMSE	Theil's U	RMSE	Theil's U	RMSE	Theil's U
ARMA	5.4105	0.4402	5.0878	0.4090	3.3787	0.2648
	Oil future contract 1					
ARMAX	5.5995	0.4533	5.3622	0.4311	3.5781	0.2805
VAR	5.3969	0.4369	5.0829	0.4087	3.3923	0.2659
VECM	**5.3942**	**0.4367**	5.0658	0.4073	3.3001	0.2587
	Oil future contract 3					
ARMAX	5.4180	0.4386	5.1098	0.4108	3.3989	0.2664
VAR	5.4433	0.4406	5.1051	0.4104	3.3663	0.2638
VECM	5.4212	0.4389	**5.0649**	**0.4072**	**3.2995**	**0.2587**

Note: The bold numbers indicate the smallest RMSE or Theil's U in the prediction of different ports' bunker prices.

Comparing the one-step-ahead forecast with the four-step-ahead forecast, using the VECM model, crude oil future contract 1 has a better performance on MGO price in the one-step forward forecast, while in the four-step forward forecast, crude oil future contract 3 has a slightly better performance than crude oil future contract 1.

4.4. Robustness Checks

To test whether the above conclusions are reliable, this section adjusts the forecast period to a total of 72 weeks from 17 July 2020 to 26 November 2021 to test whether the above conclusions are robust under the condition of shortening the time window. In the robustness test, the out-of-sample forecast is still divided into one-step -ahead and four-step-ahead; the forecast performance is shown in Tables 8 and 9.

Table 8. 1-step-ahead Prediction Performance (17 July 2020–26 November 2021, 72 observations).

	Rotterdam		**Singapore**		**Fujairah**	
	RMSE	Theil's U	RMSE	Theil's U	RMSE	Theil's U
ARMA	3.5594	0.2880	3.1600	0.2545	2.3303	0.1838
	Oil future contract 1					
ARMAX	3.6294	0.2937	3.1740	0.2556	2.3673	0.1867
VAR	3.5808	0.2898	3.1719	0.2555	2.3445	0.1849
VECM	**3.4966**	**0.2829**	**3.1330**	**0.2523**	**2.2928**	**0.1808**
	Oil future contract 3					
ARMAX	3.6564	0.2959	3.2840	0.2645	2.3948	0.1889
VAR	3.5864	0.2902	3.3116	0.2667	2.3770	0.1875
VECM	3.5720	0.2890	3.3294	0.2681	2.3420	0.1847

Note: The bold numbers indicate the smallest RMSE or Theil's U in the prediction of different ports' bunker prices.

Table 9. 4-step-ahead Prediction Performance (17 July 2020–26 November 2021, 72 observations).

	Rotterdam		**Singapore**		**Fujairah**	
	RMSE	Theil's U	RMSE	Theil's	RMSE	Theil's
ARMA	3.5714	0.2890	3.2442	0.2613	2.3945	0.1889
	Oil future contract 1					
ARMAX	3.5606	0.2881	3.2421	0.2611	2.4026	0.1895
VAR	3.5607	0.2881	3.2347	0.2605	2.3924	0.1887
VECM	3.5560	0.2878	3.2222	0.2596	2.3278	0.1836
	Oil future contract 3					
ARMAX	3.5545	0.2876	3.2108	0.2586	2.3940	0.1888
VAR	3.5712	0.2890	3.2248	0.2598	2.4093	0.1901
VECM	**3.5348**	**0.2860**	**3.1598**	**0.2545**	**2.3139**	**0.1825**

Note: The bold numbers indicate the smallest RMSE or Theil's U in the prediction of different ports' bunker prices.

In the one-step-ahead forecast, when using ARMA, ARMAX, VAR, and VECM models to forecast the price of MGO, the effect of using the ARMA model to forecast the price of MGO is better than that of the ARMAX model, which indicates that considering the yield of crude oil futures can reduce the forecast performance of the model. In the relationship between crude oil future contract 1 and MGO price, the VECM model with cointegration constraint is still better than other models. In crude oil future contract 3, With respect to the forecast of MGO price of Rotterdam and Fujairah, VECM performs slightly better than the other two models. The ARMAX model performs slightly better than the VAR and VECM in the forecast of the MGO price of Singapore. The prediction performances of MGO prices using ARMA, ARMAX, and VECM models are consistent with the results obtained in Table 5, which indicates that the VECM model has good prediction performance. Moreover, oil future contract 1 is effective in one-step-ahead prediction. The RMSE and Theil's U values of crude oil futures contract 1 are smaller than those of crude oil futures contract 3, indicating that the cointegration relationship between crude oil future contract 1 and MGO has a good prediction effect on MGO.

In the four-step-ahead prediction, the prediction effect of the ARMA model is slightly lower than the other three models. The VECM model considering the cointegration relationship between MGO return rate and crude oil future contract 3 is better in predicting MGO prices. Comparing Table 6 with Table 8, the results of futures contracts with better performance are inconsistent for the MGO price forecast of Rotterdam, the results of crude oil future contract 3 used in the MGO price forecast of other ports are consistent. In addition, it is consistent in its superior performance in the MGO price forecast that the VECM model is based on the cointegration relationship between crude oil futures contracts and MGO. Although contract 3 performs better in four-step-ahead prediction in most cases, but this paper still recommends using both contract 1 and 3 to predict four-step-ahead values since contract 3 is not better than contract 1 in Rotterdam.

In light of the above analysis, it can be shown that the result that VECM performs better than other models is robust and consistent irrespective of how the prediction window is chosen. In other words, the MGO price can be more accurately predicted when a one-step-ahead prediction is made using the crude oil future contract 1. With the four-step-ahead prediction, crude oil future contract 3 outperforms crude oil futures contract 1, but only by a small margin. In the one-step-ahead forecast and the four-step-ahead forecast, the cointegration relationship is helpful in the forecast of MGO price.

5. Discussion

5.1. Impulse Response Analysis

5.1.1. Impulse Response Function

Impulse response analysis traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. It indicates how the shocks or impulses are transmitted to each variable. Considering the moving average (MA) representation of a VAR process, that is

$$Y_t = C + \sum_{i=1}^{\infty} \Phi_i \varepsilon_{t-i} \tag{11}$$

where $\Phi_i = \sum_{i=1}^{i} \Phi_{i-1} A_i$ and A_i are fixed $(K \times K)$ matrix of coefficient parameters in the VAR model. $\Phi_0 = I_K$ and $A_i = 0$ for $i > p, i = 1, 2, \ldots$. Here K is the number of endogenous variables and p is the lag order. The $(K \times K)$ MA coefficients represent the impulse response sequences of innovations in the system. In other words, for a period of h shock, the impulse response function:

$$Y_{t+h} = C + \sum_{i=1}^{\infty} \Phi_i \varepsilon_{t+h-i} \tag{12}$$

$$\{\Phi_h\}_{i,j} = \frac{\partial y_{i,t+h}}{\partial \varepsilon_{j,t}} \tag{13}$$

Can be described as the response of $y_{i,t+h}$ resulting from a one standard deviation in the impulse of $y_{i,t}$. The inverse of the Cholesky factor of the residual covariance matrix is used to orthogonalize the impulses.

5.1.2. Analysis

In this paper, Figure 2 is an impulse response diagram based on the VAR model. It shows the reaction of MGO price at each port after being impacted by one standard deviation of crude oil futures price. As can be seen from the impulse response diagram on the left in Figure 2, when the price of crude oil futures contract 1 changes positively, the MGO price of Rotterdam presents positive feedback for two consecutive periods and tends to decrease after reaching the peak value in the second period. Then it presents negative feedback in the third period, presents positive feedback and reaches another peak value in the fourth period and basically converges to 0 after the seventh period, returning to the initial steady state. Singapore and Fujairah's MGO prices react almost exactly the same as Rotterdam's to the positive change in the crude oil futures contract 1.

When there is a positive price change in crude oil future contract 3, the bunker price of Rotterdam presents positive feedback for two consecutive periods, gradually falling after reaching the peak in the second period, the feedback disappears after the fifth period and tends to be stable. When the price of crude oil future contract 3 changes positively, the price of MGO in Singapore shows positive feedback in the first two periods and peaks in the second period, then gradually converges after a downward trend, converges to zero after the fifth period, and returns to a steady state. The reaction of the MGO price in Fujairah after the rise in crude oil future contract 3 is different from that of the other two ports. The positive feedback in the first two phases reached a peak in the second phase, but the reaction was not as intense as that in the other two ports. Then the reaction showed a downward trend. In the third phase, the positive feedback reappeared. After reaching a small peak in the fourth phase, it gradually fell back. After the eighth phase, the feedback effect of crude oil futures on it disappeared and returned to a steady state. From the above analysis, it can be seen that the rise and fall of crude oil futures price will play a positive, negative, or inhibitory role in the rise and fall of bunker oil price.

5.2. Cointegration Analysis between VLSFO and Crude Oil Future

Since 1 January 2020, the sulfur limit for bunker fuel outside the emission control zone has been reduced from not more than 3.5% to no more than 0.5% globally to prevent air pollution caused by ships. With the implementation of the IMO's Global Sulphur Restriction Order in 2020, shipping companies have taken steps to use low-sulfur bunker oil, install tail gas desulfurization devices or use alternative energy sources as power sources. Compared with the first measure, the use of latter two measures are limited. For example, the installation of desulfurization units requires the discharge of wastewater, which is restricted by the regulations of some countries in the world. New energy sources are used as the power fuel for the operation of ships. However, there are few suitable types of equipment, which is somewhat limited. At present, the main fuel of most international navigation ships is low-sulfur fuel oil, which is a directly available compliance product. Accordingly, the demand for low-sulfur bunker fuel oil will increase and the consumption will increase.

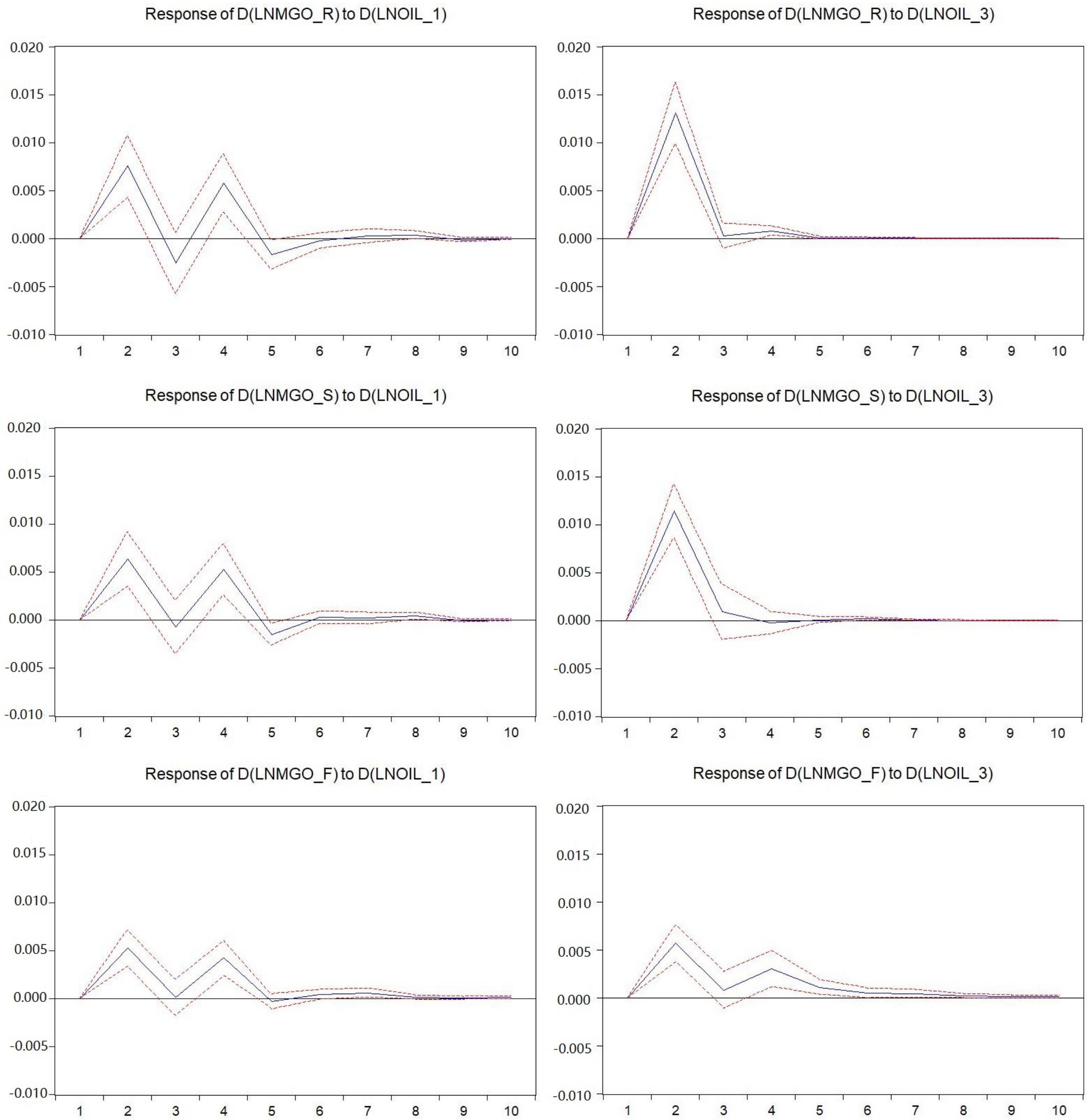

Figure 2. Response to Cholesky One S.D. (d.f. adjusted) Innovations ±2 S.E.

VLSFO is the ultra-low sulfur fuel oil obtained by directly refining low-sulfur crude oil or by desulfurizing high-sulfur fuel oil. In this case, the ultra-low sulfur fuel oil is more expensive than the high-sulfur fuel oil. Since the International Maritime Sulphur Restriction Order came into effect in January 2020, the price gap between high-sulfur fuel oil and low-sulfur fuel oil remains wide, even exceeding the US $150. The main reason is the strong demand for low-sulfur fuel oil and the tight supply. Since the implementation of the

Global Sulphur Restriction Order, the consumption of VLSFO has increased, but all ports began to provide VLSFO prices just from the second half of 2019. The price sample is small. As VLSFO can be regarded as the result of reprocessing HSFO, we generated simulation data of VLSFO prices from January 2015 to August 2019 based on the price relationship between VLSFO and HSFO from September 2019 to February 2020. The simulation data is used to test the potential cointegration relationship between VLSFO and crude oil futures.

The results of the cointegration test of the VLSFO and the crude oil futures are shown in Table 10. In the cointegration test between the crude oil future contract 1 and the VLSFO prices of Rotterdam, Singapore, and Fujairah, both Trace and the Maximum eigenvalue tests firmly reject the hypothesis of no cointegration at the 5% significance level. On the other hand, the null hypothesis that one cointegration relation exists cannot be rejected between crude oil future contract 1 and the VLSFO prices. For crude oil future contract 3, the null hypothesis of no cointegration cannot be rejected. It means there is no cointegration relation between crude oil futures contract 3 and the VLSFO prices. Crude oil future contract 1 has a cointegration relationship with VLSFO, which can be useful in the price prediction of VLSFO prices. Based on the previous empirical analysis of MGO prices, if there are enough data, it is possible to forecast the VLSFO prices in the future based on the cointegration relationship between VLSFO and crude oil future contract 1.

Table 10. The Johansen test results for VLSFO and crude oil future.

	H0	TRACE	EIGENV	LAG
	Oil future contract 1			
Rotterdam	r = 0 *	33.6248	29.7657	1
	r = 1	3.8591	3.8591	1
Singapore	r = 0 *	36.9681	34.0930	1
	r = 1	2.8751	2.8751	1
Fujairah	r = 0 *	23.4196	19.7493	2
	r = 1	3.6703	3.6703	2
	Oil future contract 3			
Rotterdam	r = 0	13.8906	9.7870	1
	r = 1	4.1036	4.1036	1
Singapore	r = 0	13.8839	10.2185	2
	r = 1	3.6654	3.6654	2
Fujairah	r = 0	13.7044	9.6641	2
	r = 1	4.0403	4.0403	2

Note: (1) The lag order is determined by BIC. (2) * denotes rejection of the hypothesis at the 0.05 level.

6. Concluding Remarks

This study aimed to investigate whether oil future prices can indicate future bunker prices. We find there is a cointegration relationship between bunker and crude oil future prices. We also considered two oil future contracts (contract 1 and 3) to find out which future contract implies the bunker price better. We find bunker price and oil future price are cointegrated, which means there is a long-run relationship between bunker and oil future prices. In a further step, we take ARMA as the benchmark model and use ARMAX, VAR, and VECM models to predict bunker price. Among those models, only VECM considers the long-run relationship between bunker and oil future prices. The model estimation results of these models (as shown in Table 4) show how the oil futures price implies the bunker price. The prediction performances of the models are compared with one-step-ahead and four-step-ahead prediction. The results show that in the one-step-ahead and four-step-ahead prediction, the VECM model established with crude oil futures contract 1 has better prediction performance than other model specifications. We also change the prediction samples to check the robustness. Finally, impulse response analysis shows the response of bunker prices to crude oil future prices in different periods.

The research of this paper is mainly to help shipping enterprises adjust bunker oil refueling plan in time according to the change of crude oil futures price, or use crude oil futures to hedge the business risk caused by an excessive change in bunker price. Given the small amount of VLSFO data currently available, this paper only investigates the cointegration relationship between its prices and crude oil future prices. In the future, the cointegration relationship may be used to forecast VLSFO prices.

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Abbreviations

The following abbreviations are used in this manuscript:

MGO	Marine Gas Oil
VLSFO	Very Low Sulfur Fuel Oil

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