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Research Article

The price behavior of the MGO bunker market: An integrated causality and interpretive structural modeling approach

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Abstract
Marine fuel price differences of supply centers have a significant effect on operators' budgets, and so are closely monitored by traders, charterers, and shipowners. The aim of this study is to determine the volatility spillovers between the prices of the major fuel centers in the world and to form a hierarchical structure based on the influence and dependence powers of these centers. For this purpose, an integrated structure of causality in variance and Interpretive Structural Modeling (ISM) methods are used. The data set used in this study includes marine gas oil (MGO) prices for 8 fuel centers used extensively in the world, namely: Fujairah, Hong Kong, Houston, Istanbul, New York, Piraeus, Rotterdam, and Singapore. This data consists of 782 daily observations, covering a 3-year-period between 14.04.2017 and 13.04.2020. The ISM results reveal that these fuel centers lie at six different levels based on their driving and dependence powers, that the sources of price volatility in the market are Fujairah and Singapore, and that the center that is most affected by volatility is Piraeus. In addition to drawing a macro frame for the fuel market, the results obtained are thought to be useful in reducing risk in the market due to uncertainty for stakeholders.

1. Introduction

Bunkering is a vital part of the shipping industry. Global bunker volume reaches about 4.3 million barrels per day (EIA, 2019). This accounts for a significant part of shipowners' budgets as a single item (Fagerholt et al., 2010; Stopford, 2013). Purchasing bunker is a critical stage for shipping operations, not only because of its cost, but also due to location and quality (Lam et al., 2011). Marine fuels are available across the world. However, price and quality fluctuate greatly in different regions.

The volatility of bunker prices creates pressure on shipowners and charterers. Bunker price fluctuations directly affect shipowners' and charterers' profit margins (Alizadeh et al., 2004). Depending on the bunker price, speed, and fuel consumption specifications of the ships (Andersson, et al., 2015), bunker costs may form between 30 and 80 % of the total costs related to a voyage (Mietzner, 2015, p. 109). The planning of bunkering operations is crucial, not only to save on voyage cost, but also to be prepared for regional fuel compliance as implemented in Emission Control Areas (ECA). As marine fuels are available globally, competition between supply locations is inevitable. On the same day, bunker prices can differ from one to another by up to 60 USD per

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ton (Yao et al., 2012). Bunkering price is a crucial item for location choice or bunker management planning. From the shipowner or charterer perspective, price difference could cause a significant negative effect on profit margins. On the supplier side, it could be an important drawback, as they may lose their competitiveness. Bunker traders play an important role in this process, as they follow markets and global economic variables closely. The bunkering hubs of Rotterdam, Fujairah, Houston, and Singapore have different prices, and they affect the prices at nearby ports accordingly, mainly due to the supply and demand ratio (Stefanakos & Schinas, 2014). The interaction of the bunkering price among these bunkering hubs is a critical stage for the shipping business due to its global nature, which in turn leads to important decision making in terms of operations, trading, charter party agreements, hedging, bunker adjustment factors, and bunker management.

Based on the bunker pricing literature, two research gaps were identified. Firstly, what are the relationships concerning bunker prices between the major bunkering ports? Secondly, which bunkering ports are more effective than others in terms of pricing? The study aims to address these gaps by proposing a method to understand price fluctuations; this was done by investigating if there is a relation among important bunker hubs globally, and also by determining which ports are the main drivers of the market in terms of bunker pricing. New marine fuels have been introduced to the market in order to comply with the International Maritime Organization (IMO) 2020 global sulfur cap. Therefore, in order to use the most current available data up to April 2020, MGO historical time series were employed, as this was already available in all markets before and after January 2020 as a 0.5 % sulfur cap compliant fuel. A novel integrated approach was adopted to investigate this subject; causality in variance analysis for the detection of bidirectional volatility spillovers, and the Interpretive Structural Modelling (ISM) method to form a hierarchical structure. Major ports and relatively smaller but important bunkering hubs were investigated together to explore their relations. Two research questions were formulated in order to address research objectives: (i) Is there a volatility spillover among the prices of major bunker centers in the world? (ii) Which are the dominant centers from which volatility spreads in the market, which are the dependent centers exposed to this volatility, and which are the transmitter centers? The results obtained revealed that there are significant volatility and risk spillovers among the prices of the eight major bunker centers in the world, and these centers are positioned at six different levels in the ISM model. Some centers are positioned at the bottom, with high impact power and low dependency, while some centers are at the top, with low impact power and high dependency. The most effective centers are Fujairah and Singapore, which are the sources of all volatilities. It can be said that the prices in the market are determined according to these centers. Istanbul and Piraeus are weak centers in terms of affecting the market, as they set their prices by following other centers, and all the volatility spillovers end in these centers. The remaining centers are positioned as linking centers, because they transfer the spillovers they receive to the market. Our study is thought to be an original study in terms of examining the econometric relationship between bunker prices and presenting these relationships in a hierarchical structure by drawing a macro framework.

In the second section of this study, the literature, consisting of studies on fuel, is summarized, and our study is positioned. The methods applied within the framework of our research questions are introduced in the third section. The data set used in the study is examined in the fourth section. After the results obtained from the analyses are presented and discussed in the fourth section, evaluations are made in the last section.

2. Literature review

There are number of studies in maritime literature which focus on bunkering price. Stefanakos and Schinas (2014) proposed a model for the forecasting of marine fuel prices. Their study took into account different bunkering hubs' time series data in order to verify the relationship between HSFO and LSFO prices. Another bunker price study investigated the relation between bunker price and vessel speeds in the dry bulk market (Acik & Baser, 2018). The impact of bunker price over Very Large Crude Carrier (VLCC) spot rates was investigated by Devanney (2011), who looked at time charter equivalent and world scale rate compared with fuel oil prices in Fujairah, taking into account daily consumption of VLCCs' speed curve. The fuzzy time series forecasting technique in predicting bunker price was explored by Stefenakos and Schinas (2015). Rotterdam, Houston, Fujairah, and Singapore weekly time series data were examined for different grades of marine fuels: 380cSt (high and low sulfur), 180cSt (high sulfur), marine diesel oil (MDO), and marine gas oil (MGO) (Stefanakos & Schinas, 2015). This study focused on major ports, and relatively small but important bunkering hubs were not investigated.

Alizadeh et al. (2004) investigated the effectiveness of hedging bunker price fluctuations in Singapore, Rotterdam, and Houston by using crude oil and petroleum contracts. Their study examined relations by applying the vector error correction model (VECM) for the cointegration of bunker prices and petroleum features with a generalized auto-regressive conditional heteroscedasticity (GARCH) error structure (Alizadeh et al., 2004). They found that the effectiveness of hedging had different dynamics in different regions; for Singapore and Rotterdam, the main dynamic was IPE crude oil futures, whereas for Houston, it was gas oil.

The bunker adjustment factor (BAF) is another tool in shipping that takes into account fuel price. It is also referred to as bunker surcharge (DHL, 2020). BAF basically allows carriers to transfer almost all increased bunker costs to the shipper in liner shipping. The relation of BAF with bunkering price was investigated in Wolff and Cariou's research. Their study used Granger casualty tests to detect any relation between BAF and bunkering prices in Rotterdam and Singapore (Cariou & Wolff, 2006). Wang et al. (2011) investigated these controversial BAF implications by collecting the relevant evidence from liner carriers, such as bunker prices, vessel speeds, and fuel costs. Their research findings indicated that carriers prefer to raise bunker surcharges rather than reduce vessel speeds to cut bunker consumption. Moreover, BAF could have strong long-term implications for the costs and fuel consumptions of liner shipping (Wang et al., 2011).

Pedrielli et al. (2015) explored bunkering contracts under fuel price and consumption uncertainty with a game theory approach. Their study explored bunker contract parameters optimization in terms of contract length and fuel price. The study of Lam et al. (2011) investigated the competitiveness of ports as bunkering hubs, based on Singapore and Shanghai. Their research determined ten attributes for the selection of bunkering ports through in-depth interviews. Afterwards, questionnaires were applied and interviews were conducted at the third stage. Their study argued that bunker price, bunker quality, and market transparency are the top factors for port selection. Acosta et al. (2011) investigated bunkering competitiveness at the Straits of Gibraltar. Their study explored expert views and took into account bunker price, the quality of the bunker, and the quality of service. However, as in Lam et al.'s (2011) study, the reasons for price difference was not part of their research objectives. Other studies in the bunkering literature concentrate on optimization problems for bunkering port selection while taking into account bunker price (De et al., 2019; Sheng et al., 2014; Vilhelmsen et al., 2013; Wang et al., 2014).

There are limited studies in the maritime literature that apply the casualty invariance method (Hsiao et al., 2014; Alizadeh, 2013; Benali & Feki, 2020). The ISM method is widely used in supply chain literature. However, its application to maritime econometrics is not known to the researchers. Bunker price dynamics have been discussed in the literature from different perspectives, as indicated above. However, this study, using the integrated method we have employed is, to the best of the authors' knowledge, the only study which focuses on the reason for bunker price fluctuations of supply ports, investigating if they affect each other and their volatility spillover.

3. Methodology

In this study, the integrated version of causality in variance and the Interpretive Structural Modeling (ISM) methods were used. The reason is that it is insufficient to identify only the relations between the centers in the market in terms of drawing the macro frame, and it is also necessary to identify the hierarchical structure of this relationship network. Causality analysis can be used to detect relationships between couples. For example, if it is applied between variables A, B, and C, some outcomes are obtained, such as variable A being the cause of variable B, variable B being the cause of variable C, variable A being the cause of variable C or not, or vice versa. However, applying causality analysis alone cannot provide the result that variable A first affects variable B, and then the effect from A is transferred to C by B. Such complex relationships exist in systems formed between some elements in the real world. For this reason, we tried to identify the possible complex structure between bunker prices by integrating the causality analysis management with the ISM method. Thus, we aimed to obtain a model that consists of dominant centers that affect the market the most at the bottom and dependent centers that are most affected at the top. The model proposed in the research is presented in **Figure 1**. First of all, bi-directional causality in variance relationships between the major bunker centers in the world were tested in all possible combinations, and a relationship matrix was formed. Then, the causal relationship network was transformed into a Structural Self-Interaction Matrix (SSIM) in order to be used in the ISM methodology. Then, the methodology was followed to form a hierarchical model and MICMAC graph. Finally, the findings were evaluated.

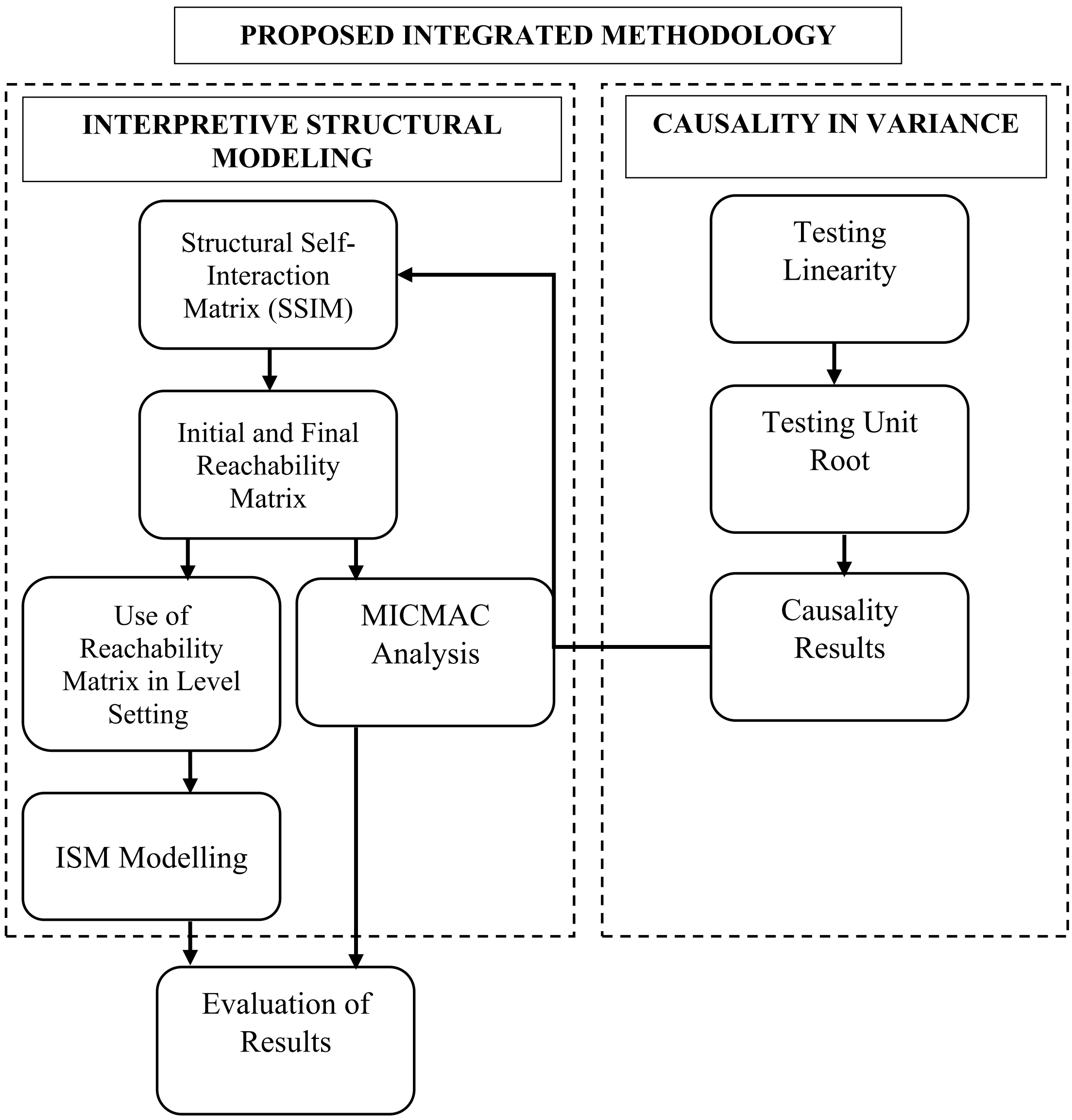

Figure 1 Research model.

1.1 Causality in variance

Volatility and risk spillover among variables are important factors in the formation of the price mechanism and the analysis of the information flow. Volatility is a concept related to price and is used to measure the uncontrolled extent of price change or asset return (Gilbert & Morgan, 2011, p. 45). It can be stated that there may be three reasons for the volatility in commodity prices; (i) information flows, (ii) economic variables related to supply and demand conditions, and (iii) market structure (Hoffman, 2011, p. 120). In this study, we mainly addressed volatility in terms of information flow. Since the change in the variance of the variable contains information about how new information comes in and how it is evaluated (Cheung & Ng, 1996), examining the relationship between the variances provides important information in determining volatility and risk spillover. One of the analyses developed in this framework is the causality in variance analysis. This method was originally developed by Cheung and Ng (1996). The idea behind the method was the cross-correlation function (CCF) of squared univariate GARCH residuals estimates. However, this method could have problems with the corresponding test statistics in different types of volatility in relatively small samples (Nouira et al., 2018). To overcome these shortcomings, Hafner and Herwartz (2006) developed a method and adopted a structure based on the Lagrange Multiplier (LM) principle. Also, the robustness of the LM approach against former issues was checked using the Monte Carlo simulation (Nazlioglu et al., 2013).

Another advantage of the method used is that it can detect nonlinear relationships. The spread of information in the globalizing world is very high, which increases the impact of unexpected events and shocks on the financial series. Thus, the normal distributions of the series deteriorate, and their structures diverge from linearity (Bildirici & Turkmen, 2015). Since the variances become time-dependent, and the fixed variance assumption is disrupted as a result of these events, making analysis using linear methods may result in erroneous results (Månsson & Shukur, 2009). In this study, reaching the results with a nonlinear method by testing the linearity of the series is aimed for.

To test nonlinearity in the series, Brock, Dechert, Scheinkman (BDS) Independence (Brock et al., 1987) was used. In addition, autoregressive conditional heteroscedasticity (ARCH) test (Engle, 1982) was also used as a complementary method to test linearity. In order to test the linearity of the series, the series were first converted into a return series by using log difference. Then, in order to separate the deterministic parts of the model and obtain stochastic parts, the most suitable autoregressive moving averages (ARMA) (p, q) model for each variable was determined based on the lowest Akaike Information Criterion (AIC) value, and the residuals of the models were separated. Finally, BDS Independence and ARCH tests were applied to the residues, and the linearity of the series was tested. Additionally, the series had to be stationary in order to apply the causality in variance test. Therefore, augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) unit root and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) stationarity tests were applied to the data used in this study.

1.2 Interpretive Structural Modeling (ISM) method

The ISM method makes it possible to sort and assign directions among the elements of a complex system (Sage, 1977). It allows for the identification of priorities and hierarchical relationships among factors in a particular network of relationships (Yudatama et al., 2018). It allows for the definition of the structure of relationships by using dependencies and driving forces between variables (Luthara et al., 2015). Thus, it provides understanding into the structure of macro-scale relationships (Chuang et al., 2013). It can be used for many types of inter-relationship interaction, such as intention, priority, contribution, reinforcement, and mathematical dependence. Elements in the system are structured in terms of interrelationships, such as dependence, influence, and consultation (Krishnaswamy et al., 2009, p. 91).

In the ISM method, firstly, factors are compared to each other in order to determine their relationships. Then, a Structural Self-Interaction Matrix (SSIM) is obtained based on the evaluations among these factors. In this matrix, the relationships between factors are generally represented by the symbols "V", "A", "X", and "O". The matrix is formed by using the following symbol rules;

- "V" for the one-way relationship from factor i to factor j
- "A" for the one-way relationship from factor j to factor i
- "X" for bidirectional relationship between factors
- and "O" for no relationship between factors

Then, an Initial Reachability Matrix (IRM) is obtained by following these rules;

- if (i, j) in the SSIM equals "V", (i, j) equals 1 and (j, i) equals 0
- if (i, j) in the SSIM equals "A", (i, j) equals 0 and (j, i) equals 1
- if (i, j) in the SSIM equals "X", (i, j) equals 1 and (j, i) equals 1
- if (i, j) in the SSIM equals "O", (i, j) equals 0 and (j, i) equals 0

After the IRM is obtained, "Driving Power" with row totals and "Dependence Power" with column totals are obtained in order to form a Final Reachability Matrix (FRM). These values indicate the position of the relevant factor in the relationship network and can be graphed for use in MICMAC (Matrices d'Impacts Croises Multiplication Appliqué a un Classement) analysis to better explain this visually. The ISM model is used to present the hierarchical structure. In order to form the model, the factors that are influenced by the selected one (Reachability) and the factors that influence this selected one (Antecedent) are listed for each factor through the FRM. Then, those factors mutual to these two lists are included in the "Intersection" list, and the factors that have the same elements in this list and the "Reachability" list are positioned at level 1. The factor(s) that is positioned in any level is removed from the lists, and each situation where matching is achieved is determined as a new level, and the factors are grouped. The hierarchical structure is represented by the final ISM model. The bottom factor in this structure is the most dominant and effective in the relationship network, while the top one is the most ineffective and dependent. In addition, the analysis can be enriched by positioning factors based on their "Driving Power" and "Dependence Power" as "Independent", "Dependent", "Autonomous", and "Linkage" through MICMAC analysis. "Independent" factors are the dominant factors with high impact and low dependency. Those which are "Dependent" are weak factors with low impact and high dependency. Those with "Autonomous" are relatively free factors that have both low impact and low dependency. Those which are "Linkage" are factors that have both high impact and high dependence and transfer the effects on them to the others.

4. Data

The data set used in this study included marine gas oil (MGO) prices for eight fuel centers used extensively in the world, namely: Fujairah, Hong Kong, Houston, Istanbul, New York, Piraeus, Rotterdam, and Singapore, in alphabetical order. There are also other large centers, but the main factor in choosing these centers was data availability. The dataset consists of 782 daily observations, covering the 3-year-period between 14.04.2017 and 13.04.2020. A graphical representation of the bunker centers discussed is presented in **Figure 2**. It can be said that bunker prices generally follow a parallel course, as the main determining factor in pricing is oil prices. As can be seen in the last part of the graph, bunker prices have dropped significantly as a result of recently falling oil prices.

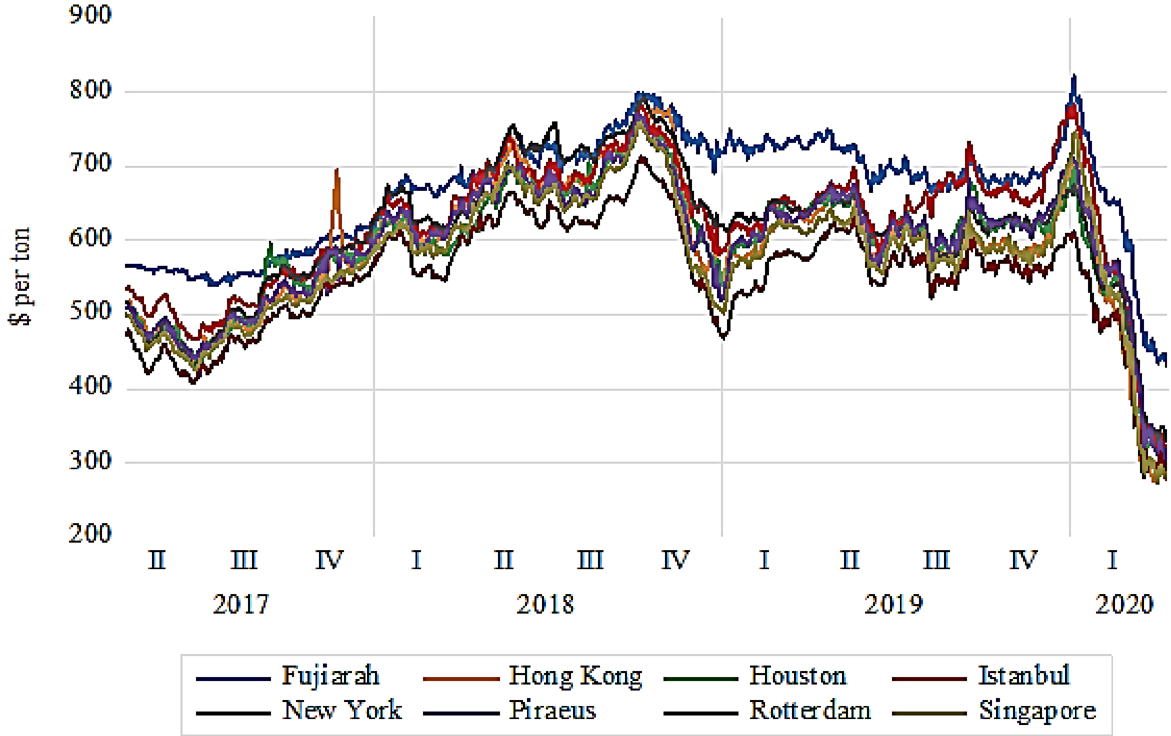

Figure 2 Historical movement of prices.
Source: Ship and Bunker (2020).

Although bunker price statistics are presented as a net value by some sources, bunkering is a pooled resource. For this reason, discounts can be applied to the prices according to the quantity, or a lower-upper limit can be determined against too-volatile prices (Farina et al., 2014). However, we based our study on the prices offered by the source, because otherwise it would be very difficult to apply an analysis in accordance with our methodology.

Descriptive statistics of the bunker prices are presented in **Table 1**. Considering the average prices in the period discussed, it is seen that the highest pricing was in Fujairah (668.18 USD), and then in Istanbul (623.49 USD), while the lowest pricing was observed in Rotterdam (550.53 USD), followed by Singapore (579.17 USD). Although the highest average price was in Fujairah, its lowest standard deviation can be interpreted as it having more stable prices than the others. Bunker price volatility in these centers can also be commented on by looking at the ratio of the standard deviation to the average. It is 11.6 % for Fujairah, 16.0 % for Hong Kong, 14.1 % for Houston, 14.2 % for Istanbul, 15.0 % for New York, 14.1 % for Piraeus, 14.6 % for Rotterdam, and 15.3 % for Singapore. In proportion to standard deviations, the lowest volatility was detected for Fujairah, and the highest volatility for Hong Kong.

Table 1 Descriptive statistics of the dataset.

	Fujairah	Hong Kong	Houston	Istanbul	New York	Piraeus	Rotterdam	Singapore
Mean	668.18	592.63	596.18	623.40	612.63	598.26	550.53	579.17
Median	687.50	598.50	612.50	645.25	625.25	615.25	561.75	589.25
Max.	822.00	777.00	766.00	782.50	793.00	771.00	712.00	757.50
Min.	430.50	275.00	298.50	312.00	322.50	303.00	280.00	272.00
Std. Dev.	77.19	94.71	83.78	88.75	92.12	84.48	80.27	88.59
Skew.	-0.77	-0.81	-0.97	-1.01	-0.67	-0.94	-0.88	-0.85
Kurt.	3.00	4.33	4.32	4.25	3.50	4.15	4.12	4.34
J.B.	77.61	143.89	179.28	182.76	65.93	159.57	140.87	152.12
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	782	782	782	782	782	782	782	782

Source: Ship and Bunker (2020).

As seen in **Figure 2**, the movements of the prices of bunker centers are very similar. To determine which centers' price movements are closer to each other, we examined the correlations of the return series and present them in **Table 2**. The reason why we look at the correlation of the return series is the unit root tests presented in **Table 3**. In order to apply analyses with series, the first differences must be taken. According to the results obtained, the correlation between all prices is significant and positive at 1 %. However, the correlation coefficients are high among some centers, and moderate among other centers. The reason for this may be the delay in the information flows, due to the possible hierarchical structure that we examined in our research.

Table 2 Correlations between return series.

	Fujairah	Hong Kong	Houston	Istanbul	New York	Piraeus	Rotterdam	Singapore
Fujairah	1.00							
Hong Kong	0.82***	1.00						
Houston	0.50***	0.51***	1.00					
Istanbul	0.74***	0.75***	0.55***	1.00				
New York	0.57***	0.59***	0.66***	0.68***	1.00			
Piraeus	0.61***	0.60***	0.56***	0.70***	0.55***	1.00		
Rotterdam	0.80***	0.78***	0.46***	0.74***	0.51***	0.57***	1.00	
Singapore	0.82***	0.82***	0.42***	0.68***	0.52***	0.53***	0.83***	1.00

*** indicates that the correlation coefficient is significant at 1 %.

5. Results and discussion

Before the analysis, the logarithms of the series were first taken, as the discrete series would become continuous and the processability of the data would become easier. Also, better distribution properties could be obtained. Since the causality in variance test requires stationarity (Hacihasanoglu et al., 2012; Nazlioglu et al., 2016), unit root tests were applied first. In addition, as it is a nonlinear method, a linearity test was applied to the series. In line with the findings obtained from these tests, causality analysis was applied and the ISM model was designed.

5.1 Causality results

Since the series had to be stationary in order to apply causality test in variance, ADF and KPSS tests were applied to the series, and the results are presented in **Table 3**. The null hypothesis of the ADF test indicates the unit root, while the null hypothesis of the KPSS test indicates stationarity. According to ADF test results, the null of unit root hypothesis could not be rejected at the level for all variables. When looking at the first differences of the series, the null of unit root hypothesis could be rejected. In the KPSS test results, this test being applied as a confirmatory measure, the null of the stationarity hypothesis was rejected at the level for all variables, but it could not be rejected in the first differences. All these results indicated that the first differences of all data should be used in the analysis. It can also be concluded that the series carried the shocks they received and did not tend to return to their mean. The main reason for this situation may have been the production policies of the countries that have most of the oil reserves, which resulted in permanent shocks in bunker prices. After the analysis of the stationarity of the series, their linearity was tested.

Table 3 Unit root test results.

		Level		First Difference	
		Constant	**Intercept & Trend**	**Constant**	**Intercept & Trend**
ADF	**Fujairah**	-0.563764	2.718556	-6.485323***	-30.64684***
	Hong Kong	0.657372	0.837451	-10.58180***	-10.87807***
	Houston	0.572393	2.503028	-12.62989***	-12.93442***
	Istanbul	-0.316625	3.312866	-6.555105***	-6.923003***
	New York	-0.624195	-0.146924	-6.718256***	-7.116791***
	Piraeus	0.933789	1.478542	-7.706124***	-28.24652***
	Rotterdam	-1.111059	-0.842603	-6.987889***	-7.254932***
	Singapore	-1.524789	-1.061858	-5.415516***	-5.712754***
KPSS	**Fujairah**	1.721130	0.994347	0.932556	0.197774***
	Hong Kong	0.838173	0.835917	0.699519***	0.144648**
	Houston	0.976162	0.859186	0.695388***	0.145167**
	Istanbul	0.936735	0.698308	0.790606	0.205145***
	New York	1.073456	1.020067	0.860872	0.153931***
	Piraeus	0.973187	0.799449	0.688776***	0.154160***
	Rotterdam	0.853525	0.833873	0.780136	0.148112***
	Singapore	0.797497	0.738673	0.639676***	0.151179***

ADF Critical Values -3.438583 for ***1 %, -2.865064 for **5 %, -2.568702 for *10 % at Intercept, -3.969860 for ***1 %, -3.415588 for **5 %, -3.130033 for *10 % at Intercept and Trend. KPSS Critical Values 0.739000 for ***99 %, 0.463000 for **95 %, 0.347000 for *90 % at Intercept, 0.216000 for ***99 %, 0.146000 for **95 %, -0.119000 for *90 % at Intercept and Trend. Quadratic Spectral Kernel and Newey-West Bandwidth are used.

After determining and estimating the most suitable ARMA (p, q) models for all the variables by using return series, BDS Independence Test was applied. Also, the ARCH test was applied as a confirmatory test. The selected most suitable ARMA models with the smallest AIC values for each variable are presented in **Table 4**.

Table 4 Selected ARMA models.

MODEL	Fuj.	H. K.	Hou.	Ist.	N. Y.	Pir.	Rot.	Sin.
ARMA (p, q)	(10, 6)	(12, 8)	(7, 10)	(10, 10)	(9, 11)	(11, 8)	(12, 11)	(10, 9)
AIC	-6.210	-6.029	-5.759	-5.837	-6.535	-5.337	-5.524	-5.913

When the models were estimated by the least squares method, it was seen that all models were significant and AR and MA roots were less than 1. When the ARCH effects in the residuals of the models were tested, the presence of the effect in various lags was confirmed in all models. The results of the BDS test applied to the extracted residuals of the models are presented in **Table 5**. The results revealed that the null hypothesis of the BDS Independence test was rejected in all dimensions of all variables, which indicated that all the variables included have nonlinear structures. Moreover, these results also showed that all the price variables discussed are not efficient in weak form considering the Efficient Market Hypothesis. This shows that prices do not move randomly; they are related to past values, and they are predictable. After testing the linearity of the variables, causality in variance tests were applied.

Table 5 Linearity test results.

Dimension	Fujairah	Hong Kong	Houston	Istanbul	New York	Piraeus	Rotterdam	Singapore
2	6.072*	8.479*	6.813*	5.865*	7.469*	7.581*	9.478*	7.795*
3	6.795*	11.125*	7.393*	6.745*	8.615*	8.021*	10.929*	9.639*
4	7.684*	12.364*	7.930*	6.948*	9.504*	8.171*	12.361*	9.826*
5	8.346*	13.478*	8.684*	7.437*	9.899*	8.480*	13.612*	10.933*
6	8.937*	14.373*	9.246*	7.833*	10.322*	8.750*	14.516*	12.037*

Null of linearity is rejected at *1 %.

Causality in variance tests were applied to include all possibilities among the eight bunker centers subject to this research. The applied causality results are presented in **Table 6**. The results showed that the null of non-causality hypothesis was rejected in a large number of combinations, and that there were significant causal relationships between the prices of many bunker centers. According to the causality in variance analysis results, there were volatility spillovers and risk transfers among many centers. However, making evaluations only according to the results of this method may be insufficient to determine the center of volatility and risk. For instance, Hong Kong seems to affect many prices; however Hong Kong is also affected by many prices. This situation can be evaluated as this center being an intermediary center in volatility and risk spread. In order to evaluate the market mechanism in the bunker market more easily, the application of the ISM method was considered as a practical tool. In this framework, after obtaining the causality analysis results, the ISM method was implemented.

Table 6 Causality test results.

		TO							
		Fujairah	Hong Kong	Houston	Istanbul	New York	Piraeus	Rotterdam	Singapore
FROM	Fujairah	X	4.48*	8.58***	4.49*	23.50***	2.15	2.71	4.20
	Hong Kong	12.05***	X	2.96	25.66***	5.11*	8.66***	20.46***	3.97
	Houston	4.32	35.16***	X	11.79***	4.41	7.60**	8.22***	0.74
	Istanbul	2.48	2.84	31.98***	X	34.44***	5.98**	1.54	3.94
	New York	0.53	18.08***	3.82	5.69**	X	5.60*	3.03	7.27**
	Piraeus	0.20	31.91***	1.01	3.59	1.06	X	1.40	7.44**
	Rotterdam	4.34	1.83	18.77***	3.40	30.15***	3.59	X	2.63
	Singapore	1.15	23.89***	19.61***	8.09**	28.02***	4.83*	4.20	X

Null of noncausality is rejected at ***1 %, **5 %, *10 %.

5.2 ISM results

In the ISM method, causality in variance test results were taken as the basis of the interactions between variables. Based on the causal relationships between the prices of bunker centers presented in **Table 6**, the SSIM was formed, and is presented in **Table 7**. Relations are modeled through the symbols mentioned in the methodology section.

Table 7 Structural Self-Interaction Matrix (SSIM).

	Fujairah	Hong Kong	Houston	Istanbul	New York	Piraeus	Rotterdam	Singapore
Fujairah		X	V	V	V	O	O	O
Hong Kong			A	V	X	X	V	A
Houston				X	O	V	X	A
Istanbul					X	V	O	A
New York						V	A	X
Piraeus							O	X
Rotterdam								O
Singapore								

Within the framework of the relationship network modeled in the SSIM table, the relationships between the variables are digitized to be "1" if there is a relationship, or "0" if there is no relationship, and these are presented in **Table 8**. This table shows the IRM results, and FRM was obtained with row and column totals. Row totals are defined as the "Driving Power" because these totals show how much the related bunker center affects the other centers, and column totals are defined as the "Dependence Power" because these totals show how much the related bunker center is affected by the other centers. According to this table, the centers with the highest driving power stand out as Singapore and Hong Kong, while the centers with the highest dependency power stand out as Hong Kong, Istanbul, New York, and Piraeus. These comments are covered in more detail in the MICMAC analysis. After creating the FRM matrix, level determination analysis was applied for the bunker centers by examining their relationships with other centers.

Table 8 Initial and Final Reachability Matrix.

	Fuj.	H. K.	Hou.	Ist.	N.Y.	Pir.	Rot.	Sin.	DRIVER
Fujairah	1	1	1	1	1	0	0	0	**5**
Hong Kong	1	1	0	1	1	1	1	0	**6**
Houston	0	1	1	1	0	1	1	0	**5**
Istanbul	0	0	1	1	1	1	0	0	**4**
New York	0	1	0	1	1	1	0	1	**5**
Piraeus	0	1	0	0	0	1	0	1	**3**
Rotterdam	0	0	1	0	1	0	1	0	**3**
Singapore	0	1	1	1	1	1	0	1	**6**
DEPENDENCE	**2**	**6**	**5**	**6**	**6**	**6**	**3**	**3**	

"Reachability" and "Antecedent" values for level determination were established using FRM and are presented in **Table 9**. The numbers in the table correspond to the order of the bunker centers in the table. "Reachability" values include the centers affected by the related center, while "Antecedent" values include the centers that affect the related center. "Intersection" values, formed by the intersection of these two lists, were formed, and level determination was applied. Piraeus was positioned at the first level, and at the end of a step-by-step process, all eight centers were placed into six distinct levels. The ISM model was formed according to the determined levels and the relationship network.

Table 9 Use of the reachability matrix in level determination.

		Reachability	Antecedent	Intersection	Level
1	**Fujairah**	1, 2, 3, 4, 5	1, 2	1, 2	**6**
2	**Hong Kong**	1, 2, 4, 5, 6, 7	1, 2, 3, 5, 6, 8	1, 2, 5, 6	**4**
3	**Houston**	2, 3, 4, 6, 7	1, 3, 4, 7, 8	3, 4, 7	**5**
4	**Istanbul**	3, 4, 5, 6	1, 2, 3, 4, 5, 8	3, 4, 5	**2**
5	**New York**	2, 4, 5, 6, 8	1, 2, 4, 5, 7, 8	2, 4, 5, 8	**2**
6	**Piraeus**	2, 6, 8	2, 3, 4, 5, 6, 8	2, 6, 8	**1**
7	**Rotterdam**	3, 5, 7	2, 3, 7	3, 7	**3**
8	**Singapore**	2, 3, 4, 5, 6, 8	5, 6, 8	5, 6, 8	**6**

The ISM model which emerged after determining levels is presented in **Figure 3**. According to this model, Fujairah and Singapore bunker centers are located at the bottom of the model. This indicates that the source of price volatility in the market is due to these two bunker centers. These volatilities and risks in this level spread to other centers. Moreover, it can be said that other centers determined their pricing by following the prices of these two centers. The center with the least impact on the market and which is greatly affected by the volatility of prices in other centers was identified as Piraeus. Price volatility in this center had no effect on any other center. After Piraeus, the most dependent centers were identified as Istanbul and New York.

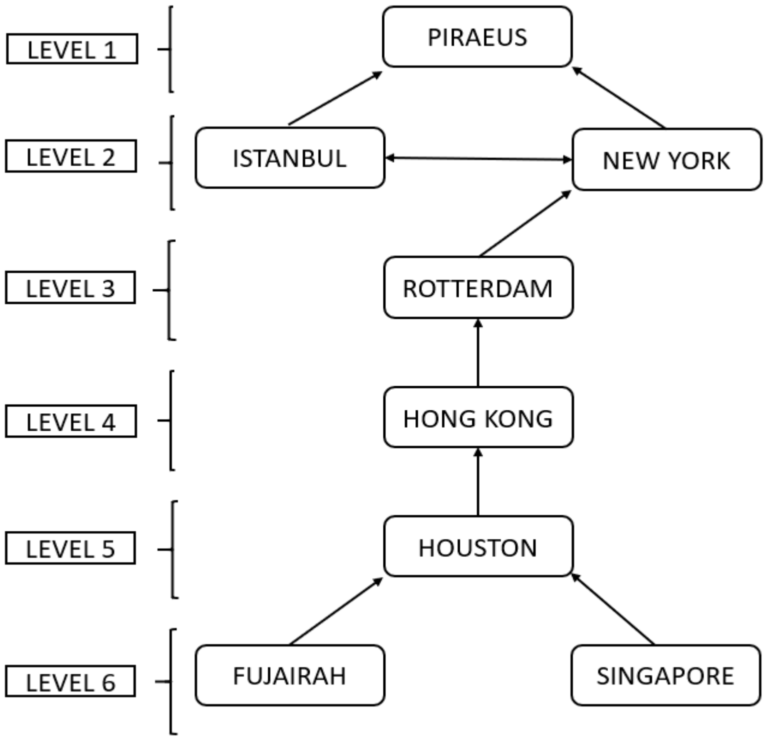

Figure 3 ISM model.

The positions within the relationship network can be seen more clearly in the MICMAC analysis. With MICMAC analysis, the positions of the bunker centers on the chart are grouped under four different cluster heads, as presented in **Figure 4**. Fujairah and Singapore, which are situated at the bottom of the ISM model and have big impacts on the volatility of the market prices, are naturally located in the "Independent" cluster on the chart. As a feature of this cluster, it contains bunker centers with low dependency and high impact power. In this respect, the prices in the centers here are determined independently, and volatility in their prices spreads to other markets. Another cluster that has a high impact power is "Linkage", but those in this cluster also have high dependencies. Therefore, they significantly affect the rest of the market, while simultaneously are dependent on those in the "Independent" cluster. In a way, they transmit the volatility and risk spread which they are exposed to. The bunker centers of New York, Houston, and Hong Kong are positioned in this cluster. Another cluster with high dependency is the "Dependent" cluster. The bunker centers in this cluster have high dependency and low impact power. In other words, they have low power to affect prices in the market so, consequently, they are at the top in the ISM model. The results revealed that the bunker centers of Piraeus and Istanbul are positioned in this cluster. Although Istanbul is on the border in terms of dependency, it was found appropriate for it to be positioned in the "Dependent" cluster, considering its position in the ISM model and its intersection value in FRM. Finally, the "Autonomous" cluster, which has both low dependency and low impact power, was examined. The volatility of the fuel centers in this section is less affected by other centers, and has low effect on the other centers. As seen in the figure, only the Rotterdam bunker center is positioned in this cluster.

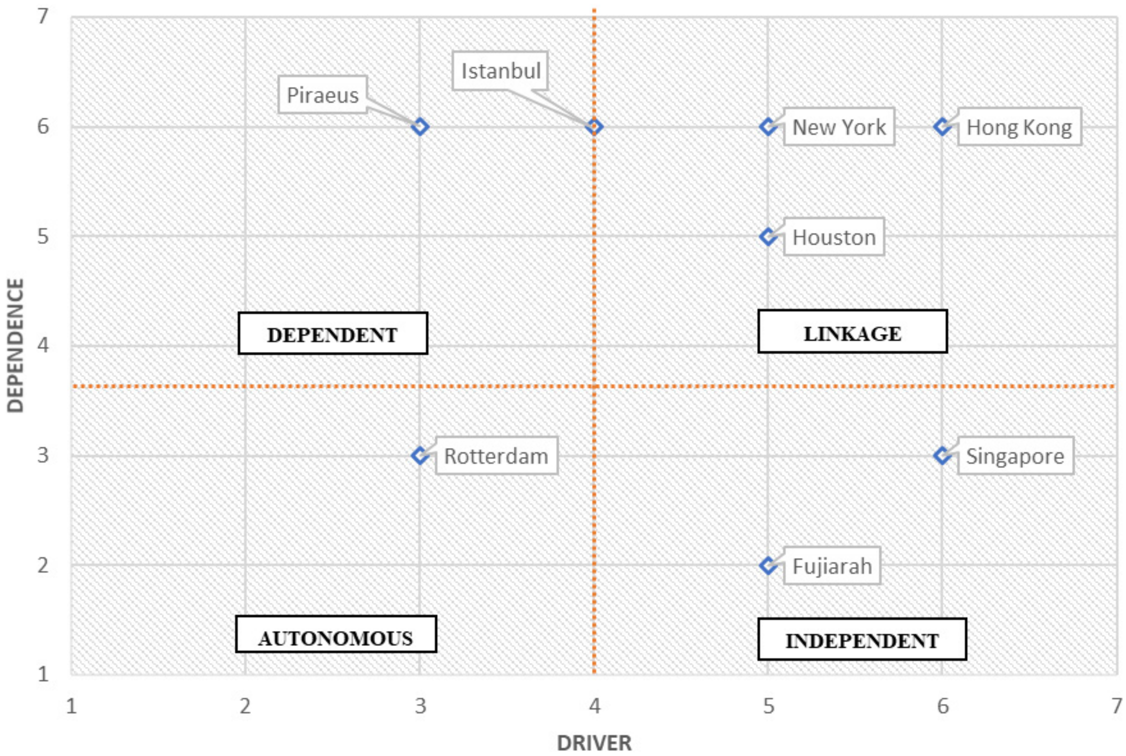

Figure 4 MICMAC analysis.

IMO 2020 regulations have had a significant effect on bunkering. The availability and the quality of compliant fuel (maximum 0.5 % sulfur content) brings another dimension to the marine fuel markets. Shipowners need to be well organized to avoid penalties or higher costs at bunker purchases. Our results show that Singapore and Fujairah are both independent supply points and drive the market. Singapore's driving capability is slightly higher than Fujairah while, in contrast, Fujairah is less dependent than Singapore. Lam et al. (2011) argue that local market structure, storage capacity, and not relying on bunker imports provide price advantage. Fujairah, taking advantage of being in an oil-rich area, along with refinery capacity, is a good fit for Lam et al. (2011) argument. However, Singapore's case is slightly different from this. Singapore is a net importer of crude oil to run their refineries, and they are dependent on fuel oil imports in order to meet bunkering demand. Having significant marine traffic, storage capacity, blending services, trading activities, and competition between suppliers makes Singapore 'independent', with its reduced dependency and strong driver capability. Houston's driving capacity is as strong as Fujairah, since it has substantial oil refinery capacity that has a significant effect on the market. However, its high dependency score implies that Houston, while driving the rest of the market, follows Fujairah and Singapore in terms of bunker pricing. Similar dynamics are implied for New York. Regional refineries and pipelines from the Gulf Coast both provide 35 to 40 % of liquid fuel to New York, with the remaining volume being imported (Meyers et al., 2013). Its strong driving capacity is weakened by its high dependency. Hong Kong, like Singapore, is an important hub in terms of shipping activity, and our empirical results indicate that Hong Kong has a significant driving effect on bunkering price. 75 % of Hong Kong's fuel oil imports are provided by Singapore, and 48 % of gasoline imports are from mainland China (Hong Kong Census and Statistics Department, 2019). Hong Kong was revealed in our analysis to have a 'high dependency' score. Hong Kong's considerable marine traffic and high potential bunker supply volume is weakened by its dependency and, thus, its bunker price follows Singapore, Fujairah, and Houston. The port of

Rotterdam is the largest port in Europe, with five oil refineries (PoR, 2020). Storage, blending capabilities, the ability to provide alternative fuels such as liquefied natural gas (LNG) or Bio Fuels, being an intermodal transport center, and having a high volume of bunkering activities bring Rotterdam to the unique position of being 'autonomous'. Although its dependency is as low as Singapore, Rotterdam is not in a strong position in terms of market driving capacity. Istanbul and Piraeus are positioned in the 'dependent' corner of the table. Istanbul's driving capacity is slightly better than Piraeus; its geographical location controlling the Black Sea to Mediterranean traffic and its refinery and storage facilities in its vicinity could be responsible for this difference over Piraeus.

6. Conclusions

This study followed a novel approach, consisting of the integration of causality in variance analysis and ISM analysis. The relationship between the MGO prices of the major bunker centers in the world was examined by causality in variance analysis, because the hierarchical structure of the volatility spillovers between prices is important for understanding the market structure being investigated. The study by Stefanakos (2015) explored bunker prices for major ports; however, the relationships of other important bunker hubs, such as Piraeus and Istanbul, and their interdependency, were not evaluated. The topics examined in the literature included bunker port competitiveness (Lam et al., 2011), forecasting bunkering price (Stefanakos & Schinas, 2015; Stefanakos & Schinas, 2014), and hedging (Alizadeh et al., 2004). The lack of a study approaching the subject in this regard in the literature was the motivation of the researchers.

Factors such as supply, demand, and some unexpected events are also effective in determining bunker prices. However, in accordance with the method used, we applied our analysis assuming that prices carry this information, since even the smallest events are reflected in prices and carried as information. The results obtained by econometric analysis alone demonstrate the significant econometric relationships between certain centers and indicates volatility spillovers. However, this spillover may have come to the relevant center from another center, and then been transferred to another one. Also, it is natural that the volatility in prices arises from dominant centers in the bunker market, since there are only a certain number of sellers in the market. Moreover, in the BDS test, which is one of the interim applications conducted during this research process, it was determined that the prices of all the bunker centers were not effective in a weak form, according to EMH. This shows that prices do not move randomly, and that not all information is reflected in prices. In other words, prices may be controlled by certain centers. For all these reasons, after obtaining econometric results, we aimed to form a hierarchical structure using ISM analysis.

The results of the econometric analysis showed that there are significant causalities between some centers, which indicates volatility spillovers, risk transmissions, and price flow, since causality in variance points to the flow of information. After the relationship network matrix was formed according to the causality results, these relationships between the centers were designated hierarchically using ISM modeling. The ISM analysis presented results that allowed for the examination of the results from two different aspects; the first was ISM modeling, and the second was MICMAC analysis. According to ISM modeling, the Fujairah and Singapore bunker centers are located at the bottom of a model consisting of six levels. This result shows that these two centers are independent in terms of volatility spillover, and that their power to influence the market is very high. Piraeus is located at the top of this model, which shows that the volatility in all markets is reflected in the prices at Piraeus. Istanbul and New York are located under Piraeus. Via the application of MICMAC analysis, bunker centers were placed into four sections. In line with the ISM model, the Fujairah and Singapore centers appear in the "Independent" section, which includes those with high effect power and low dependence. New York, Hong Kong, and Houston appear in the "Linkage" section, where the power of both effect and dependence are high. Piraeus and Istanbul, on the other hand, are located in the "Dependent" section, where the dependency effect is high and the power effect is low. Finally, Rotterdam, unlike the other centers, appears in the "Autonomous" section, which has a low level of both dependency and effect. According to these results, the most effective centers are Fujairah and Singapore, which are the sources of all volatilities. It can be said that the prices in the market are determined according to these centers. Secondly, New York, Hong Kong, and Houston centers can also be said to be highly effective centers, because they transfer the spillovers they receive to the market and affect many centers. Istanbul and Piraeus are weak centers in terms of affecting the market, as they set their prices by following other centers, and all the volatility spillovers end in these centers.

This study proposes a model to identify the price relations of bunkering ports and to determine the information flow among them. Bunker management is critical for effective ship management. Lack of proper management could lead to significant losses in profit margins, as well as penalties if vessels need to consume non-compliant fuels. Analyzing the bunker price relations of major supply ports provides guidance for bunker traders, shipowners, and charterers. Financial tools such as hedging and bunkering contracts, as well as implications of bunker adjustment factors, bring bunker price behaviors to the center of negotiations. This study provides a benchmark for marine fuel market price behaviors. Bunker supply strategies of charterers and shipowners are critical for their profit margins, as fuel cost takes the leading expenditure along with crew wages. Liner shipping activities are performed between scheduled ports, and shipowners and charterers can organize their budgets for bunkering while using some tools such as bunker hedging. However, vessels in the spot market rarely have the opportunity to use these tools if they are operated by mid/small scale shipowners. Bunker lift quantity is subject to distance to be travelled and the cost. Trade-off between these parameters is traditionally controlled by the bunker supply strategy for shipowners and charterers. However, the emission control measures of the IMO add other dimensions for bunkering strategies, such as fuel stability, compatibility, and availability. Fuel availability, potential increase on bunker cost, safety risk, stability of the bunker, and compatibility are the main challenges for IMO 2020. HSFO, VLSFO, or alternative fuels such as LNG, ammonia, or hydrogen will be in service at the same time, and stakeholders in shipping should take their positions accordingly. Bunker suppliers want to see the market for new developments, and take long term infrastructure decisions accordingly, in a highly competitive market. On the other hand, shipowners and charterers seek flexibility which makes them free to take the most profitable voyages (Doymus & Sakar, 2020). As emission control measures are getting stricter, this new dimension could provide opportunity for those bunkering locations, such as Peiraeus and Istanbul, which are defined as 'dependent' according to research findings. As availability is a critical concern for VLSFO, HSFO, or alternative fuels, providing products in different segments reduces their dependence and approach to a more autonomous position. Rotterdam's 'autonomous' profile is expected to be strengthened with its infrastructure for alternative fuels and to sustain its unique position as a bunker supply location. Moreover, Rotterdam could place on the 'independent' side of the MICMAC table in certain fuel segments, such as LNG, with its strong infrastructure and market coverage. For the 'linkage' locations, Houston, New York, and Hong Kong have strong driver capability, but dependent natures. In addition to the cost and distance parameters of the bunker management strategies, adding an alternative fuels segment could make them highly competitive. The research findings indicate that Fujairah and Singapore are independent supply locations in terms of driver and dependence level, as discussed above. As the fuel transition is in progress, these two locations need to follow these new trends to keep their competitive positions as they gain through geographical location and cost.

The ports in the study were selected according to data availability; some important bunkering hubs, such as Busan, Gibraltar, Panama, or Zhoushan, were not analyzed in the study. Another limitation of the study was related to the length of the data set, since older high-frequency data could not be accessed. If longer data sets were obtained, possible breaks over time could also be considered, and changes in the market system could also be monitored. The study was conducted only for MGO. In accordance with these limitations, future studies may also consider using longer series of data and different types of marine fuel, such as Very Low Sulphur Fuel (VLSFO), heavy fuel oil (HFO), and liquefied natural gas (LNG). The IMO 2020 and Covid 19 effects on bunker price could be another interesting future research topic in order to contribute to the maritime industry.

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