NOVEL SHIPPING COMPETITIVENESS INDEX USING ORDERED WEIGHTED AVERAGE OPERATOR

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Abstract

There is limited research on the sustainable development of maritime economies, and on the role of maritime transport in those economies. At most, we can find some isolated case studies that fail to explore the dependencies across factors. In some of our previous works, we introduced indices assessing the national and the beneficial fleet competitiveness and their connection with several factors that influence the role of shipping for a given country. Here, we extend this research and create models only with significant variables, as well as propose a new index to rank countries based on shipping competitiveness that utilizes the ordered-weighted average operator. We demonstrate in detail our methodology. We also test our new index and compare its efficiency with previously developed indices using a data set for 84 maritime countries. We clearly demonstrate the advantages of the new ordinary weighted average operator index.

Keywords (3-5 words): linear regression; national fleet; beneficial fleet; influential factors

1. Introduction and background

The shipping industry has a long history, with the first cargoes being moved by sea more than 5,000 years ago [Stopford, 2009]. It is estimated that 80% of the international cargo is transported by ship [UNCTAD, 2017]. Internationally, shipping is the key means of supplying raw materials, consumer goods, and energy, becoming a facilitator of world business and contributing to economic evolution and employment, both at sea and on land [McKinley et al., 2019]. The top five ship-owning economies combined accounted for 52% of world fleet tonnage [UNCTAD, 2017]. The importance of national shipping has received growing attention for several reasons outlined in [Nguyen et al., 2019]. The development of the blue economy [CSIRO, 2015] has emphasized further the understanding of the connection between economic development and sustainable shipping. The amount of research on national shipping, specifically on broader maritime sector and blue economy is limited and expands to the introduction of the ocean economy [Spalding, 2016], which includes aspects of renewable energy, seabed mining, ocean restoration, blue biotechnology, etc. Another area of discussion around the importance of shipping to the global economic arena is the notion of the maritime cluster. It incorporates the large shipping, marine, and port operations industries and is a spatially bounded organisational form where co-location and geographical proximity encourage the formation of interactive networks between organizations [Doloreux 2017]. Despite the existing trend of de-globalization and regionalization [Hee-Yeon 2017], maritime clusters still hold their strategic significance in the maritime arena.

Continuing our research from three previous papers - Nguyen (2011), Nguyen & Bandara (2015), and Nguyen et al. (2019), we develop further our exploration on how we measure national shipping competitiveness and its relation to various factors (international trade, shipping history, policy, registration, oil exports, technology development, etc.). In the previous three works, we explored two measures of national shipping – national fleet and beneficial fleet over data for 84 maritime countries. Here, we aim to identify the significant variables over national competitiveness and propose a new shipping competitiveness index based on an ordered-weighted average operator. Our paper makes contributions both in terms of analyzing literature in shipping competitiveness and in terms of the computational tools adaptable to problems of how we measure shipping competitiveness. In what follows, section 2 we provide the background of our new index, and identify the variables utilized in this and the previous ranking indices. Section 3 justifies the ordinary weighted average index, and section 4 presents in detail our methodology and new indices. Section 5 gives substantial details on the ranking results with our new indices for the 84 maritime countries. Section 6 concludes the paper.

2. Models and variables for shipping competitiveness

To create a shipping competitiveness index (SCI), we need to find a connection between several factors that influence the role of shipping for each country, measured by the natural logarithms of the deadweight tonnage of national fleet (V=LnFleet) and of the deadweight tonnage of beneficial fleet (W=LnBen). The beneficial fleet is the fleet owned and operated by companies located in the country [UNCTAD, 2014]. We have identified 4 binary and 13 continuous factors, given in the column 1 of Table 1. The meaning and origin of those are described as follows: parameters from 1 to 12 are given in [Nguyen, Bandara, 2015]; parameters 13, 16 and 17 are given in [Nguyen, 2011]; parameters 14 and 15 are given in [Nguyen et al., 2019].

For simplicity, the above-described factors are short-written as the variables X_j (j=1,2,…,17), given in column 2 of Table 1. Let the values of the variables V, W, and X_j are known for N countries, denoted as v_i, w_i, and $x_{i,j}$ for the i-th country. We can construct a linear regression model of some proxy for the shipping competitiveness of a given country depending on several of the factors above and take as a criterion the predicted value minus the constant term. By doing so, we can improve the measurement process by smoothing errors and inconsistencies modeled by the residual terms in the regressions. The rank of the acquired predicted value of a given country is assumed to be the country's shipping competitiveness index. By selecting different proxies, we can obtain a family of SCIs based on linear regression models.

In [Nguyen, 2011] a NAT-SCI is proposed, where the LnFleet (national fleet) is regressed on 2 binary and 10 continuous variables (see column 3 of Table 1). In [Nguyen, Bandara, 2015], a BEN-SCI is proposed, where the LnBen (beneficial fleet) is regressed on 4 binary and 9 continuous variables (see column 4 of Table 1). A similar model is developed for LnFleet as well. To overcome the problem of aligning the two basic criteria for the national shipping (V and W), two new proxy variables were introduced in the same paper: combined SCI (C-SCI) and weighted SCI (W-SCI). The first one uses the sum of LnFleet and LnBen as a dependent variable whereas the second uses the weighted sum of LnFleet and LnBen as a proxy for shipping competitiveness. The sets of independent variables are shown respectively in columns 5 & 6 of Table 1. In [Nguyen et al., 2019] an adaptive SCI (A-SCI) is applied to solve the problem with the unknown weights of the two criteria, where LnFleet is regressed on LnBen and on the 15 variables from column 7 of Table 1. Then, the proxy variable is calculated as the predicted value of LnFleet minus the constant term and minus the LnBen term. All criteria are using full regression models with slope coefficients for any independent variable indicated in Table 1.

The objectives of this paper are on one hand to create models only with significant variables and on the other hand to propose a novel proxy for the SCI ranking based on the ordered-weighted average operator (OWA) proposed in [Yager, 1988]. The OWA-SCI will give alternative solution to the problem with the unknown weights of the LnFleet and the LnBen basic criteria. The first objective will allow full regression diagnostics of the created models although using full regression models has its own merits. All models will use the independent variables in column 8 of Table 1.

Table 1: Independent variables utilized in the various ranking indices

Independent variable	Alias	NAT-SCI	BEN-SCI	C-SCI	W-SCI	A-SCI	OWA-SCI	Independent variable	Alias	NAT-SCI	BEN-SCI	C-SCI	W-SCI	A-SCI	OWA-SCI
Dum_OilEx	X_1		*	*	*	*	*	**LnCoastline**	X_{10}	*	*	*	*	*	*
Dum_TopOilEx	X_2	*	*	*	*	*	*	**LnPolicy**	X_{11}	*	*	*	*	*	*
Dum_TopOilIm	X_3		*	*	*	*	*	**LnReg**	X_{12}	*	*	*	*	*	*
Dum_Flag	X_4	*	*	*	*	*	*	**LnGDPCap**	X_{13}		*	*	*	*	*
FinDev	X_5	*	*	*	*	*	*	**LnTour**	X_{14}					*	*
LnBuild	X_6	*	*	*	*	*	*	**LnFish**	X_{15}					*	*
LnHistory	X_7	*	*	*	*	*	*	**LnGDP**	X_{16}	*					
LnTrade	X_8	*	*	*	*	*	*	**SDUM_FOC**	X_{17}	*					
LnOil_Ex	X_9	*	*	*	*	*	*								

3. Essence of the OWA operator

The OWA operator was introduced as a possible solution of the aggregation problem where t criteria C_r (r=1,2,…,t) are used to rank the elements of a given set of alternatives Z. For any $z \in Z$, the values of the criteria belong to the unit interval: $c_r = C_r(z) \in [0,1]$,for $r =,1,2,\ldots,t$. Here, c_r is the degree to which the alternative z satisfies the r^{th} criterion C_r. So, z can be described with the t-dimensional argument tuple $(c_1, c_2, \ldots, c_t)$ or equivalently, with the t-dimensional ordered argument tuple $(d_1, d_2, \ldots, d_t)$, where d_r is the r^{th} largest element of the argument tuple. Let $\vec{K}(k_1, k_2, \ldots, k_t)$ be a t-dimensional weighting vector whose elements are non-negative real numbers which sum to one. The OWA aggregation operator is defined as

$$F(z) = F(c_1, c_2, \ldots, c_t) = OWA(d_1, d_2, \ldots, d_t) = \sum_{r=1}^{t} k_r d_r \tag{1}$$

This operator transforms the t values of criteria $(c_1, c_2, \ldots, c_t)$ into a value function $F(z)$ for the alternative z. The OWA operator generalizes the ‘or’ and the ‘and’ operators and produces results which are between these two extremes. A measure of closeness of a specific OWA operator to the ‘or’-operator is called degree of “orness” [Yager, 1988]:

$$orness(\vec{K}) = orness(k_1, k_2, \ldots, k_t) = \frac{1}{t-1} \sum_{r=1}^{t} (t-r) k_r \tag{2}$$

For a discussion about the numerous applications of the OWA aggregation operator together with an excellent bibliographical review see [Emrouznejad, Marra, 2014].

4. Formal description of methodology and new indices

For simplicity of notations, we will introduce the dependent variables Y_k (k=1,2,3,4) which will serve as proxies of the shipping competitiveness as follows: Y_1=Y_3=V, Y_2=W, and Y_4=V+aW, where

a is a known positive constant. The values of Y_k for the i^{th} country will be denoted as $y_{k,i}$. We shall attempt to construct four regression models:

$$\begin{aligned} y_{1,i} = \text{LnFleet}_i = &\ \beta_{1,0} + \beta_{1,1}\text{Dum\_OilEx}_i + \beta_{1,2}\text{Dum\_TopOilEx}_i + \beta_{1,3}\text{Dum\_TopOilIm}_i \\ &+ \beta_{1,4}\text{Dum\_Flag}_i + \beta_{1,5}\text{FinDev}_i + \beta_{1,6}\text{LnBuild}_i + \beta_{1,7}\text{LnHistory}_i + \beta_{1,8}\text{LnTrade}_i \\ &+ \beta_{1,9}\text{LnOilEx}_i + \beta_{1,10}\text{LnCoastline}_i + \beta_{1,11}\text{LnPolicy}_i + \beta_{1,12}\text{LnReg}_i \\ &+ \beta_{1,13}\text{LnGDPCap}_i + \beta_{1,14}\text{LnTour}_i + \beta_{1,15}\text{LnFish}_i + u_{1,i} = \beta_{1,0} + \sum_{j=1}^{15} \beta_{1,j} x_{i,j} + u_{1,i} \end{aligned} \tag{3}$$

$$\begin{aligned} y_{2,i} = \text{LnBen}_i = &\ \beta_{2,0} + \beta_{2,1}\text{Dum\_OilEx}_i + \beta_{2,2}\text{Dum\_TopOilEx}_i + \beta_{2,3}\text{Dum\_TopOilIm}_i \\ &+ \beta_{2,4}\text{Dum\_Flag}_i + \beta_{2,5}\text{FinDev}_i + \beta_{2,6}\text{LnBuild}_i + \beta_{2,7}\text{LnHistory}_i + \beta_{2,8}\text{LnTrade}_i \\ &+ \beta_{2,9}\text{LnOilEx}_i + \beta_{2,10}\text{LnCoastline}_i + \beta_{2,11}\text{LnPolicy}_i + \beta_{2,12}\text{LnReg}_i \\ &+ \beta_{2,13}\text{LnGDPCap}_i + \beta_{2,14}\text{LnTour}_i + \beta_{2,15}\text{LnFish}_i \beta_{2,0} + u_{2,i} = \beta_{2,0} + \sum_{j=1}^{15} \beta_{2,j} x_{i,j} + u_{2,i} \end{aligned} \tag{4}$$

$$\begin{aligned} y_{3,i} = \text{LnFleet}_i = &\ \beta_{3,0} + \beta_{3,1}\text{Dum\_OilEx}_i + \beta_{3,2}\text{Dum\_TopOilEx}_i + \beta_{3,3}\text{Dum\_TopOilIm}_i \\ &+ \beta_{3,4}\text{Dum\_Flag}_i + \beta_{3,5}\text{FinDev}_i + \beta_{3,6}\text{LnBuild}_i + \beta_{3,7}\text{LnHistory}_i + \beta_{3,8}\text{LnTrade}_i \\ &+ \beta_{3,9}\text{LnOilEx}_i + \beta_{3,10}\text{LnCoastline}_i + \beta_{3,11}\text{LnPolicy}_i + \beta_{3,12}\text{LnReg}_i + \beta_{3,13}\text{LnGDPCap}_i \\ &+ \beta_{3,14}\text{LnTour}_i + \beta_{3,15}\text{LnFish}_i + \beta_{3,16} w_i + u_{3,i} = \beta_{3,0} + \sum_{j=1}^{15} \beta_{3,j} x_{i,j} + \beta_{3,16} w_i + u_{3,i} \end{aligned} \tag{5}$$

$$\begin{aligned} y_{4,i} = \text{LnFleet}_i + \beta_{3,16}\text{LnBen}_i = &\ \beta_{4,0} + \beta_{4,1}\text{Dum\_OilEx}_i + \beta_{4,2}\text{Dum\_TopOilEx}_i \\ &+ \beta_{4,3}\text{Dum\_TopOilIm}_i + \beta_{4,4}\text{Dum\_Flag}_i + \beta_{4,5}\text{FinDev}_i + \beta_{4,6}\text{LnBuild}_i + \beta_{4,7}\text{LnHistory}_i \\ &+ \beta_{4,8}\text{LnTrade}_i + \beta_{4,9}\text{LnOilEx}_i + \beta_{4,10}\text{LnCoastline}_i + \beta_{4,11}\text{LnPolicy}_i + \beta_{4,12}\text{LnReg}_i \\ &+ \beta_{4,13}\text{LnGDPCap}_i + \beta_{4,14}\text{LnTour}_i + \beta_{4,15}\text{LnFish}_i + u_{4,i} = \beta_{4,0} + \sum_{j=1}^{15} \beta_{4,j} x_{i,j} + u_{4,i} \end{aligned} \tag{6}$$

Since the value of the positive constant, a, used in Y_4 is the slope $\beta_{3,16}$ estimated in (5), it follows that the regression model (6) can be constructed after constructing the regression model (5). The four regression models will be solved using the Ordinary Least Square (OLS) method. We will obtain a Classical Normal Linear Regression Model (CNLRM) [Gujarati, 2004, pp. 107-117] provided the assumptions of nullity, homoskedasticity, normality, independence, and multicollinearity hold [Selvanathan et al., 2021, p. 791].

The necessity to use only significant coefficients comes from a sixth assumption, called linearity, which is formulated in [Lind et al, 2012]. It boils down to identifying a model with proper structure where every coefficient contributes to the precision of the predicted values and no available regressor can improve the model precision. We will use forward stepwise regression procedure to construct the CNLRM with a correct structure. It starts with a set of regressors containing only the constant term and adds one regressor at each step. The selected regressor is that one of the significant slopes which maximally increases the adjusted coefficient of determination (R^2_{adj}). The significance of each candidate regressor slope is determined by a t-test with the heteroscedasticity-consistent HC4-estimate of the slope's standard error [Cribary-Netto, 2004] which deals with possible heteroscedasticity, non-normal errors, and existence of high-leverage points. If all available slopes are selected or when no regressor is added, then the procedure stops, and the "best" structure of the regression is determined.

Let all the significant coefficients of the k^{th} model are denoted as $\beta_{k,j}=\beta_{k,j}^{*}$ (where k=1,2,3,4 and j=1,2,…,15). Since the correlation between V=LnFleet and W=LnBen is close to perfect (correlation coefficient 0.9713 over data described in the next section), the model (3) will always select W as the best regressor and therefore $\beta_{3,16}=\beta_{3,16}^{*}$ (i.e. the value of the positive constant, a, used in Y_4 will come from a significant slope).
Knowing the significant coefficients of the linear regression models (3)-(6) we can calculate several criteria for shipping competitiveness and estimate the corresponding SCI ranks for each country.
The first criterion, NAT-Crit, is equivalent to the predicted value of Y_1=LnFleet in model (3):

$$\text{NAT-Crit}_i=\sum_{\substack{j=1\\ \beta_{1,j}=\beta_{1,j}^{*}}}^{15}\beta_{1,j}^{*}x_{i,j}\Rightarrow \text{NAT-SCI}_i=rank\left(\text{NAT-Crit}_i\right) \tag{7}$$

The second criterion, BEN-Crit, is equivalent to the predicted value of Y_2=LnBen in model (4):

$$\text{BEN-Crit}_i=\sum_{\substack{j=1\\ \beta_{2,j}=\beta_{2,j}^{*}}}^{15}\beta_{2,j}^{*}x_{i,j}\Rightarrow \text{BEN-SCI}_i=rank\left(\text{BEN-Crit}_i\right) \tag{8}$$

The third criterion, A-Crit, is equivalent to the predicted value of Y_3=LnFleet from model (5) but disregarding the influence of the "independent" variable LnBen:

$$\text{A-Crit}_i=\sum_{\substack{j=1\\ \beta_{3,j}=\beta_{3,j}^{*}}}^{15}\beta_{3,j}^{*}x_{i,j}\Rightarrow \text{A-SCI}_i=rank\left(\text{A-Crit}_i\right) \tag{9}$$

The fourth criterion, W-Crit, is equivalent to the predicted value of Y_4= LnFleet +aLnBen in model (6), and the positive constant a is defined in model (5) as $a=\beta_{3,16}=\beta_{3,16}^{*}$:

$$\text{W-Crit}_i=\sum_{\substack{j=1\\ \beta_{4,j}=\beta_{4,j}^{*}}}^{15}\beta_{4,j}^{*}x_{i,j}\Rightarrow \text{W-SCI}_i=rank\left(\text{W-Crit}_i\right) \tag{10}$$

The fifth criterion, C-Crit, is the sum of the first two criteria:

$$\text{C-Crit}_i=\text{NAT-Crit}_i+\text{BEN-Crit}_i\Rightarrow \text{C-SCI}_i=rank\left(\text{C-Crit}_i\right) \tag{11}$$

The novel sixth criterion, OWA-Crit, is equivalent to an ordered-weighted average of the two basic criteria (V and W) with weights respectively 0.25 and 0.75:

$$\text{OWA-Crit}_i=\frac{100}{0.25\,max\left\{\text{NAT-SCI}_i,\text{BEN-SCI}_i\right\}+0.75\,min\left\{\text{NAT-SCI}_i,\text{BEN-SCI}_i\right\}} \tag{12}$$
$$\Rightarrow \text{OWA-SCI}_i=rank\left(\text{OWA-Crit}_i\right)$$

The theoretical minimal and maximal limits of the OWA-Crit are 100/N and 100, respectively, which can be achieved by two last rank results and by two first rank results from the NAT-SCI and BEN-SCI basic criteria. The OWA-Crit is slightly modified reciprocal of the OWA aggregation operator with t=2 criteria and with weighted vector $\vec{K}\left(0.25,0.75\right)$. The first modification is that the unit interval of the two attributes are substituted with the closed interval [1,N]. The second modification is that here our preferences decrease with the decrease of the attributes unlike the original OWA operator. That is why formula (2) will measure the degree of "andness" and the degree of "orness" will be estimated as the complement to 1 of the degree of "andness":

$$orness\left(\text{OWA-Crit}\right)=1-\frac{1}{t-1}\sum_{r=1}^{t}\left(t-r\right)k_r=1-\frac{1}{2-1}\left[\left(2-1\right)0.25+\left(2-2\right)0.75\right]=0.75 \tag{13}$$

The function $rank$(.) used in formulae from (7) to (12) is calculated as:

$$rank\left(\text{Crit}_i\right)=\sum_{\substack{j=1\\ Crit_j<Crit_i}}^{N}(1)+\frac{1}{2}\sum_{\substack{j=1\\ Crit_j=Crit_i}}^{N}(1)+\frac{1}{2} \qquad (14)$$

5. Analysis and results

We shall utilize numerical information that describes the shipping competitiveness of N=84 nations with at least relatively developed maritime industry. The properties of the data set are described in [Nguyen, et al, 2019]. The coefficients of all regression models are calculated with Singular Value Decomposition of the design matrix as described in [Press et al., 2007], where the singular values are classified using the PCCSV algorithm from [Nikolova et al. 2021]. By doing so, any harmful effect of possible multicollinearity is eliminated from the solution. The homoscedasticity of the models is tested with the MHTRA algorithm formulated in [Tenekedjiev et al., 2021] which uses an auxiliary regression model for the absolute predicted residual value. If the latter is not significant, then the original model is declared homoscedastic. If the auxiliary model is valid according to the ANOVA test, but its adjusted coefficient of determination is less than 0.25, then the original model will be labeled as heteroscedastic with practically negligible heteroscedasticity [Tenekedjiev, Radojnova, 2001]. The validity of the normality assumption is diagnosed with Jarque-Bera statistical test [Gujarati, 2004, pp. 148-149] with p-value calculated using a Monte-Carlo procedure proposed in [Tenekedjiev et al., 2021].

The stepwise regression procedure for model (3) converges in 6 steps into

$$\begin{aligned}\text{LnFleet}_i=&-12.21-0.6499\text{Dum\_OilEx}_i+0.7574\text{Dum\_TopOilEx}_i\\&+0.1060\text{LnBuild}_i+0.6227\text{LnTrade}_i+0.2317\text{LnReg}_i+u_{1,i}\end{aligned} \qquad (15)$$

The 95%-confidence interval of the standard error of the residuals is [0.963, 1.32] with point estimate 1.11. The R^2=0.805, whereas R^2_{adj}=0.792. The model is adequate with p-value of ANOVA test of less than 10^{-14}. The coefficients of the regression model are significant (Table 2), where the last column shows the contribution $\Delta R^2_{adj,j}$ of the j-th regressor to R^2_{adj}. The HC4 correlation matrix of the coefficients is given in Table 3.

Table 2. Regression coefficients in model (3)

Variable	Mean	HC4 sigma	HC4 t_stat	HC4 Pvalue	$\Delta R^2_{adj,j}$
Constant	-1.221e+01	2.566e+00	-4.757e+00	8.847e-06	0
Dum_OilEx	-6.499e-01	2.636e-01	-2.466e+00	1.587e-02	0.010
Dum_TopOilEx	7.574e-01	2.899e-01	2.612e+00	1.078e-02	0.006
LnBuild	1.060e-01	2.720e-02	3.897e+00	2.044e-04	0.121
LnTrade	6.227e-01	1.260e-01	4.944e+00	4.299e-06	0.622
LnReg	2.317e-01	8.238e-02	2.812e+00	6.226e-03	0.033

The model is homoscedastic since the auxiliary model of the absolute predicted residual value is insignificant (ANOVA p-value of 0.11) with negligible $R^2_{adj}=0.049$. The residuals are not normally distributed since the Jarque-Bera Monte-Carlo test p-value is around 0.01. That fact justifies using the HC4 estimates for the standard deviations of the model slopes.

The stepwise regression procedure for model (4) converges in 5 steps into

$$\begin{aligned}\text{LnBen}_i=&-12.90-0.5775\text{Dum\_OilEx}_i+0.1026\text{LnBuild}_i\\&+0.6417\text{LnTrade}_i+0.2594\text{LnReg}_i+u_{2,i}\end{aligned} \qquad (16)$$

The 95%-confidence interval of the standard error of the residuals is [0.902, 1.24] with point estimate 1.04. The R^2=0.826, whereas R^2_{adj}=0.817. The model is adequate with p-value of ANOVA test of less than 10^{-14}. The coefficients of the regression model are significant according to Table 4, where the last column shows the contribution $\Delta R^2_{adj,j}$ of the j-th regressor to R^2_{adj}. The HC4 correlation matrix of the coefficients is given in Table 5.

Table3.HC4-correlation matrix of the regression coefficients for model (3)

	Constant	Dum_OilEx	Dum_TopOilEx	LnBuild	LnTrade	LnReg
Constant	1.000	0.167	0.274	0.567	-0.951	0.302
Dum_OilEx	0.167	1.000	-0.191	-0.014	-0.202	0.115
Dum_TopOilEx	0.274	-0.191	1.000	0.044	-0.238	0.007
LnBuild	0.567	-0.014	0.044	1.000	-0.480	-0.141
LnTrade	-0.951	-0.202	-0.238	-0.480	1.000	-0.574
LnReg	0.302	0.115	0.007	-0.141	-0.574	1.000

The model is homoscedastic since the auxiliary model of the absolute predicted residual value is insignificant (ANOVA p-value of 0.11) with negligible $R^2_{adj} = 0.043$. The residuals are normally distributed since the Jarque-Bera Monte-Carlo test p-value is around 0.073.

Table 4. Regression coefficients in model (4)

Variable	Mean	HC4 sigma	HC4 t_stat	HC4 Pvalue	$\Delta R^2_{adj,j}$
Constant	-1.290e+01	2.371e+00	-5.442e+00	5.737e-07	0
Dum_OilEx	-5.775e-01	2.551e-01	-2.264e+00	2.634e-02	0.011
LnBuild	1.026e-01	2.855e-02	3.595e+00	5.624e-04	0.136
LnTrade	6.417e-01	1.205e-01	5.324e+00	9.277e-07	0.628
LnReg	2.594e-01	8.504e-02	3.051e+00	3.106e-03	0.042

The stepwise regression procedure for model (5) converges in 3 steps into

$$\text{LnFleet}_i = 0.1506 - 0.4228\text{Dum\_Flag}_i + 0.9726\text{LnBen}_i + u_{3,i} \quad (17)$$

The 95%-confidence interval of the standard error of the residuals is [0.504, 0.687] with point estimate 0.582. The R^2=0.945, whereas R^2_{adj}=0.943. The model is adequate with p-value of ANOVA test of less than 10^{-14}. The coefficients of the regression model are significant according to Table 6, where the last column shows the contribution $\Delta R^2_{adj,j}$ of the j-th regressor to R^2_{adj}. The HC4 correlation matrix of the coefficients is given in Table 7.

Table 5. HC4-correlation matrix of the regression coefficients for model (4)

	Constant	Dum_OilEx	LnBuild	LnTrade	LnReg
Constant	1.000	0.175	0.593	-0.944	0.343
Dum_OilEx	0.175	1.000	0.021	-0.242	0.205
LnBuild	0.593	0.021	1.000	-0.457	-0.221
LnTrade	-0.944	-0.242	-0.457	1.000	-0.624
LnReg	0.343	0.205	-0.221	-0.624	1.000

The model is practically negligibly heteroscedastic since the auxiliary model of the absolute predicted residual value is significant (ANOVA p-value of 0.0435), but with negligible $R^2_{adj} = 0.052$. The residuals are not normally distributed since the Jarque-Bera Monte-Carlo test p-value is less than 10^{-14}. That fact justifies using the HC4 estimates for the standard deviations of the model slopes. From this model, we can find the positive parameter a=0.9726, equal to the slope in front of W=LnBen in (17).

Table 6. Regression coefficients in model (5)

Variable	Mean	HC4sigma	HC4t_stat	HC4Pvalue	$\Delta R^2_{adj,j}$
Constant	1.506e-01	2.236e-01	6.735e-01	5.026e-01	0
Dum_Flag	-4.228e-01	1.701e-01	-2.485e+00	1.502e-02	0.001
Lean	9.726e-01	3.621e-02	2.686e+01	4.287e-42	0.943

The stepwise regression procedure for model (6) converges in 6 steps into

$$\begin{aligned} y_{4,i} &= \text{LnFleet}_i + 0.9726\text{LnBen}_i = -23.92 - 1.276\text{Dum\_OilEx}_i + 1.353\text{Dum\_TopOilEx}_i \\ &+ 0.2113\text{LnBuild}_i + 1.212\text{LnTrade}_i + 0.4809\text{LnReg}_i + u_{4,i} \end{aligned} \quad (18)$$

The 95%-confidence interval of the standard error of the residuals is [1.76, 2.41] with point estimate 2.04. The R^2=0.830, whereas R^2_{adj}=0.819. The model is adequate with p-value of ANOVA test of less than 10^{-14}. The coefficients of the regression model are significant according to Table 8, where the last column shows the contribution $\Delta R^2_{adj,j}$ of the *j*-th regressor to R^2_{adj}. The HC4 correlation matrix of the coefficients is given in Table 9.

Table 7. HC4-correlation matrix of the regression coefficients for model (5)

	Constant	Dum_Flag	LnBen
Constant	1.000	0.200	-0.986
Dum_Flag	0.200	1.000	-0.246
LnBen	-0.986	-0.246	1.000

The model is homoscedastic since the auxiliary model of the absolute predicted residual value is insignificant (ANOVA *p*-value of 0.084) with negligible $R^2_{adj} = 0.059$. The residuals are normally distributed since the Jarque-Bera Monte-Carlo test p-value is around 0.53.

Table 8. Regression coefficients in model (6)

Variable	Mean	HC4sigma	HC4t_stat	HC4Pvalue	$\Delta R^2_{adj,j}$
Constant	-2.392e+01	4.774e+00	-5.011e+00	3.304e-06	0
Dum_OilEx	-1.276e+00	5.000e-01	-2.552e+00	1.267e-02	0.011
Dum_TopOilEx	1.353e+00	5.783e-01	2.339e+00	2.190e-02	0.005
LnBuild	2.113e-01	5.474e-02	3.860e+00	2.328e-04	0.130
LnTrade	1.212e+00	2.393e-01	5.065e+00	2.673e-06	0.634
LnReg	4.809e-01	1.624e-01	2.960e+00	4.070e-03	0.038

The criteria and their respective SCI ranks are given in Table 10 (for the first 20 and the last 5 countries, for the sake of limitation of space). The results show that the adaptive SCI (A-SCI) with significant coefficients is unable to discriminate the countries according to their shipping competitiveness (all countries but two have the same ranking). However, the model (5) produced the value of the positive constant *a* (0.9726), which in turn allowed to calculate the weighted SCI (W-SCI). The other five indices produce practically the same results, which shows that OWA-SCI is robustly estimating the rank. However, using the latter has certain advantages. First, OWA-SCI utilizes the information in the two basic criteria unlike NAT-SCI and BEN-SCI. Second, it does not make unreasonable assumptions like equal weight of the basic criteria unlike C-SCI. Third, OWA-SCI naturally eliminates the problem of defining externally the weights of the two basic criteria unlike the W-SCI, which has to use information from A-SCI. Fourth, the work [Yager, 1988] contains a generalization of the OWA operator to deal with criteria that have equal importance, which allows flexible OWA-SCI ranking similar to the original version of the W-SCI described in [Nguyen, Bandara, 2015].

Table 9. HC4-correlation matrix of the regression coefficients for model (6)

	Constant	Dum_OilEx	Dum_TopOilEx	LnBuild	LnTrade	LnReg
Constant	1.000	0.115	0.181	0.597	-0.948	0.337
Dum_OilEx	0.115	1.000	-0.233	-0.012	-0.176	0.168
Dum_TopOilEx	0.181	-0.233	1.000	0.005	-0.166	0.047
LnBuild	0.597	-0.012	0.005	1.000	-0.482	-0.179
LnTrade	-0.948	-0.176	-0.166	-0.482	1.000	-0.609
LnReg	0.337	0.168	0.047	-0.179	-0.609	1.000

All six SCI-ranking methods rely on linear regression models. The predicted values of the outliers, poorly describe the measured dependent variable values. In our case the outliers have to be identified and the rank of an outlier country has to be flagged because the shipping competitiveness index may contain unknown level of error. We will identify separately the outliers in the models (3) and (4) by using the CODPA algorithm developed in [Nikolova et al., 2021]. CODPA is organized in cycles allowing to identify outliers with different order of magnitude. The single comparison significance level is set to 1%, whereas the selected maximum false discovery rate is 30%. The maximum number of cycles was selected to be 10. The resulting procedure conservatively defined as outliers for model (3) only Greece and Korea (both in the first cycle). For model (4), only Greece was identified as an outlier (again in the first cycle). The second cycles for the two models never discovered new outliers. It follows that the OWA-ranks of Greece and Korea are doubtful and should not be taken at face value.

Table 10. Criteria values and SCI ranks for selected countries[1]

Country	NAT-Crit	NAT-SCI	BEN-Crit	BEN-SCI	C-Crit	C-SCI	W-Crit	W-SCI	A-Crit	A-SCI	OWA-Crit	OWA-SCI
China	23.97	1	24.95	1	48.93	1	47.27	1	0	40.5	100.00	1
Germany	23.42	3	24.37	2	47.80	2	46.17	2	0	40.5	44.44	2
USA	23.46	2	23.71	6	47.17	4	46.08	3	0	40.5	33.33	3
Japan	23.26	4	24.20	3	47.45	3	45.85	4	0	40.5	30.77	4
UK	22.95	5	23.91	4	46.86	5	45.27	5	0	40.5	23.53	5
Korea	22.85	6	23.78	5	46.63	6	45.05	6	0	40.5	19.05	6
India	22.44	7	23.37	7	45.81	7	44.24	7	0	40.5	14.29	7
Singapore	22.32	9	23.36	8	45.68	8	44.06	8	0	40.5	12.12	8
Belgium	22.31	10	23.22	9	45.53	9	43.96	9	0	40.5	10.81	9
Italy	22.07	12	23.08	10	45.15	10	43.52	12	0	40.5	9.52	10
Taipei, Chinese	22.12	11	23.00	11	45.12	11	43.58	11	0	40.5	9.09	11
Russian Fed.	22.33	8	22.55	21	44.87	14	43.86	10	0	40.5	8.89	12
France	21.96	14	22.96	12	44.92	13	43.28	14	0	40.5	8.00	13
Canada	22.04	13	22.91	13	44.94	12	43.39	13	0	40.5	7.69	14
Turkey	21.95	15	22.85	14	44.80	15	43.28	15	0	40.5	7.02	15
Netherlands	21.84	18	22.83	15	44.67	16	43.04	19	0	40.5	6.35	16
Brazil	21.86	16	22.73	17	44.60	18	43.08	17	0	40.5	6.15	17.5
Norway	21.85	17	22.76	16	44.60	17	43.10	16	0	40.5	6.15	17.5
Greece	21.80	19	22.73	18	44.53	19	43.06	18	0	40.5	5.48	19
Indonesia	21.78	20	22.69	19	44.48	20	42.95	20	0	40.5	5.19	20
...												
Seychelles	15.90	81	16.65	80	32.55	80	31.32	80	0	40.5	1.25	80
Iceland	15.91	80	16.54	82	32.44	82	31.17	82	0	40.5	1.24	81
Guyana	15.90	82	16.60	81	32.50	81	31.25	81	0	40.5	1.23	82
Eritrea	15.19	83	15.85	83	31.04	83	29.85	83	0	40.5	1.20	83
Madagascar	14.75	84	15.44	84	30.19	84	28.91	84	0	40.5	1.19	84

6. Discussion and conclusions

We presented a new competitiveness index based on the OWA operator and compared its effectiveness with competitiveness indices we have presented in previous works. We tested this new index over the data about 84 maritime countries that we utilized in previous research [Nguyen et al., 2019], which also allowed us to make extensive comparisons between the new and the previously proposed indices.

The NAT-SCI (as its name suggests) is useful for the competitiveness of nationally own fleet and not for other variables, whereas the BEN-SCI is useful for the evaluation of the attractiveness of countries' shipping market. The pair W-SCI and A-SCI were presented for the sake of backward compatibility with our previous research works on the topic and also for comparison with the new index. The C-SCI and OWA-SCI are combinations of the NAT-SCI and BEN-SCI indices. We have extensively discussed the advantages of the OWA-SCI.

As direction for future studies, our findings and approaches need to be applied to a broader set of recent data for the same or for a larger pool of countries, to test and explore results and discuss in more detail the performance of specific countries from specific regions. While our work very much concentrated on presenting the competitiveness index based on the OWA operator, ad demonstrate its user over data, another important direction of future work for our study is to explore policy recommendations resulting from our findings. We need to explore how our competitiveness indices can be utilized when drafting economic, environmental, or other policies nationally and internationally. In this way our findings might be of practical use to policymakers, maritime industry representatives, etc.

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[1] The table with the results for the full list of countries is available at https://www.researchgate.net/publication/352836638_NOVEL_SHIPPING_COMPETITIVENESS_INDEX_USING_ORDERED_WEIGHTED_AVERAGE_OPERATOR_Hong-Oanh_Nguyen_Natalia_Nikolova_Levashini_Gunasegar_Kiril_Tenekedjiev_21_st_Annual_General_Assembly_-AGA_2021_The_Interna

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